Capital, Ideas, and the Costs of Financial Frictions*

Pablo Ottonello
University of Maryland, Minneapolis Fed, and NBER
ottonell@umd.edu

Thomas Winberry
Wharton and NBER
twinb@wharton.upenn.edu

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Abstract

We study the role of financial frictions in determining the allocation of investment and innovation among established U.S. firms. Empirically, we find that firms are investment-intensive when they have low net worth but become innovation-intensive as they accumulate net worth. To interpret these findings, we develop an endogenous growth model with heterogeneous firms and financial frictions. In our model, firms are investment-intensive when they have low net worth because they face a steep return schedule for capital. Financial frictions determine how quickly firms can accumulate capital, reduce its return, and shift toward innovation. This reduction in innovation generates large losses in aggregate productivity, even though the losses from capital misallocation are comparatively small. Hence, the main aggregate cost of financial frictions is that fewer new ideas are discovered, not that existing ideas go underfunded.

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1 Introduction

In the long run, economic growth is driven by new ideas that push out the technological frontier. While many of these ideas are generated by new firms entering the economy, a substantial share of new ideas are generated by established firms already in the economy. In this paper, we study the innovation decisions of these established firms because they face a distinctive tradeoff: since they already have ideas in place, these firms must decide not only how much to innovate—creating new ideas—but also how much to invest in capital—scaling up production using existing ideas. When a firm is financially constrained, these two activities will compete for the same funds within the firm. At the micro level, how do financial frictions distort the mix of investment and innovation within firms? At the macro level, do these distortions quantitatively matter for aggregate productivity?

We address these questions using firm-level evidence and an endogenous growth model with heterogeneous firms subject to financial frictions. Empirically, we find that established firms are investment-intensive when they have low net worth but become innovation-intensive as they accumulate net worth. Our model matches this finding because firms with low net worth are on the steep part of the return schedule for capital, crowding out innovation. At the micro level, financial frictions slow the rate at which firms accumulate capital, drive down its return, and shift toward innovation. At the macro level, the resulting reduction in innovation substantially lowers aggregate productivity, even though the allocation of capital across firms is relatively efficient in comparison.

Our analysis focuses on established firms that already have at least one "scalable idea," that is, an idea that requires meaningful capital investment to bring to market. In contrast, the smallest and youngest firms in the economy are focused on creating their first scalable idea and are therefore highly innovation-intensive, consistent with the empirical evidence in, for example, Akcigit and Kerr (2018). By definition, these firms do not yet face the tradeoff between investment and innovation that motivates our analysis.

Our empirical sample is drawn from Compustat, a panel of publicly listed U.S. firms. To our knowledge, Compustat is the only U.S. panel dataset that measures our outcomes of interest (investment and innovation expenditures) together with firms' financial positions.

However, Compustat is a highly selected subset of established firms because it only contains firms with publicly traded equity or debt. We address this issue by explicitly accounting for the selection into Compustat within our model.

We refer to our main empirical finding as the *pecking order of firm growth*: firms primarily grow by accumulating capital when they have low net worth, but shift toward growing by new ideas when they have high net worth. We document this finding by relating physical investment rates, R&D rates, and patenting rates to net worth using within-firm variation over time. We interpret this finding as evidence that firms prioritize investment over innovation when they are financially constrained, as proxied by having low net worth (as well as being small or young). However, the variation in net worth is endogenous, and we do not have exogenous variation to identify its causal effect on the mix of investment and innovation.

We therefore provide three pieces of supporting evidence that financial frictions play an important role in driving the pecking order. First, we show that idiosyncratic shocks that relax firms' financial constraints induce them to become more innovation-intensive, indicating the constraints delayed their shift toward innovation in the first place. Second, we show that sectors with less pledgeable assets, and therefore tighter constraints, have a steeper pecking order. Third, we provide examples from earnings calls in which firm managers explicitly discuss the role of financial frictions in the tradeoff between investment and innovation.

Motivated by this evidence, we develop a heterogeneous-firm endogenous growth model with financial constraints. Given our focus on established firms, firms in our model are initially endowed with their first scalable idea, embodied in their productivity. Firms must then decide how much to spend on investment, which increases the capital stock used in production, and how much to spend on innovation, which increases the probability of receiving a new idea and raises the firm's productivity. The mix of investment and innovation is determined by the relative return schedules for these two activities: the return to capital reflects its marginal profitability and collateral value in external finance, while the return to innovation reflects the probability of generating a new idea times the value of that idea to the firm, including any contribution to borrowing capacity.

Financial frictions create the pecking order in the model by slowing down capital accumulation, thereby delaying the shift toward innovation. Consider the typical firm dynamics in our model: firms enter the economy with low capital relative to their initial productivity, placing them on the steep part of the return schedule for capital. Firms therefore borrow as much as possible to accumulate capital and move down the return schedule. The tightness of financial frictions governs how quickly this process occurs; without financial frictions, firms would immediately jump to their optimal scale, eliminating the pecking order entirely.

We exploit these dynamics to develop a new approach to discipline the innovation technology. The standard approach uses patent realizations to proxy for the arrival of a new idea, but many ideas are not patented (see Adhami 2025). We instead use what firms reveal through their forward-looking investment decisions. In particular, our model predicts that new ideas generate investment spikes—short-lived bursts of investment—as firms adjust capital toward its new optimal scale. Consistent with this implication, R&D expenditures are strongly associated with investment spikes in the data: a one-standard-deviation increase in R&D raises the probability of a spike in the following year by approximately 30%.

We use the calibrated model to quantify the causal role of financial frictions in generating the pecking order at the firm level. The model generates a pattern of coefficients similar to the data, implying a central role for financial frictions in the pecking order. Importantly, we do not target these coefficients in the calibration; instead, we choose parameters to match moments that are independently informative about the strength of financial frictions and the other key forces within the model. We also validate the strength of our calibrated financial frictions by showing the model matches untargeted features of the distribution of free cash flows and leverage. The model does not exactly match the magnitudes of the pecking order from the data, suggesting that other forces may also play a role in the data as well.

We then use the calibrated model to quantify the macro effects of financial frictions on aggregate total factor productivity (TFP). To do so, we compute the transition path of a counterfactual economy that starts from the same state as our calibrated economy but permanently removes financial frictions. The resulting change in TFP measures the costs of the financial frictions in the initial economy or, equivalently, the gains from removing them in the counterfactual economy. We decompose these gains into two components: an innovation component, which captures how higher innovation improves the distribution of firm-level productivity, and a misallocation component, which captures improvements in the allocation of capital across firms.

Quantitatively, the gains from higher innovation account for 95% of the total gains from removing financial frictions in present value terms. The reason is that higher innovation persistently raises the growth rate of aggregate productivity, while lower misallocation only raises the level. Hence, for the current U.S. economy—corresponding to the calibrated initial condition—the main long-run cost of financial frictions is that fewer new ideas are discovered, even though good ideas are able to attract funding once they are discovered.

We show that this result is robust across a range of parameter values and modeling choices. The most important sensitivity concerns the strength of what Atkeson and Burstein (2019) call "intertemporal knowledge spillovers." In our baseline, the spillover elasticity is one, so higher innovation raises productivity *growth* in the long run. With lower elasticities, higher innovation can only raise the long-run *level* of productivity, reducing the aggregate gains from innovation. However, the gains from higher innovation remain much larger than the gains from lower misallocation across the range of elasticities considered by Atkeson, Burstein and Chatzikonstantinou (2019).

Finally, we illustrate the policy implications of financial frictions in our model. We find that an innovation subsidy raises consumption-equivalent welfare about twice as much as a budget-equivalent investment subsidy. This result reinforces our main message: since financial frictions primarily distort the economy through lower innovation, policies that stimulate innovation generate larger gains than policies that stimulate investment.

Related Literature These findings contribute to our understanding of the aggregate costs of financial frictions. The existing quantitative macro literature about financial frictions has primarily focused on how the frictions affect the allocation of inputs across firms (see, e.g., Buera, Kaboski and Shin 2011, Midrigan and Xu 2014, or Moll 2014). However, these papers abstract from innovation decisions, so the costs of financial frictions only arise from distorting inputs as a function of productivity.[1] We endogenize the distribution of productivity through firms' innovation decisions and find that the aggregate costs from lower innovation dominate the costs from misallocation.

[1] Midrigan and Xu (2014) allow financial frictions to affect whether firms enter the "modern" sector which has a better technology. This adoption margin is complementary to the innovation margin we study here.

Our model builds on the Hopenhayn (1992) framework, in which firm dynamics are determined given an exogenous process for productivity. A key feature of Hopenhayn (1992) is decreasing returns to scale, which implies that firms have an optimal scale given their level of productivity. The literature has studied how various frictions impede the ability of firms to reach this optimal scale, including financial frictions in, for example, Khan and Thomas (2013). We incorporate innovation into this class of models, endogenizing the productivity process and therefore the distribution of optimal firm size. In doing so, we are broadly related to Atkeson and Burstein (2010), who embed innovation decisions in a Melitz (2003)-style model without capital.

Our model also builds on the endogenous growth framework pioneered by Aghion and Howitt (1992) and Grossman and Helpman (1991), and more recently used in quantitative analyses by, e.g., Klette and Kortum (2004), Akcigit and Kerr (2018), or Acemoglu et al. (2018). We contribute to the growth literature by incorporating capital accumulation and sluggish input dynamics induced by financial frictions.[2]

In independent work, Sui (2025) also develops a version of the Hopenhayn (1992) model in which firms choose investment and innovation subject to financial frictions in order to study how differences in financial conditions account for differences in economic performance across European countries. We view our two papers as highly complementary. Our paper's main contribution is the pecking order of firm growth: we document it in the data, show that it is the key manifestation of financial frictions in the model, and quantitatively assess its implications for the aggregate economy.

More broadly, our findings are consistent with a large body of empirical work that provides cross-country, regional, sectoral, firm-level, and case study evidence that better-functioning financial markets lead to higher economic growth (see Levine, 2005, for a detailed survey). There is also a large body of theoretical work about the relationship between

[2]Our focus on differences in innovation intensity across firms is most closely related to Akcigit and Kerr (2018), who study how firms choose between two different types of innovation. We abstract from different types of innovation to instead study the choice between innovation and investment. In a related vein, Chen and Xu (2023) incorporate both physical capital and R&D investments into an industry equilibrium model, abstracting from financial frictions. Our results are also related to the literature on how financial frictions distort the allocation of investment across different types of capital, such as tangible vs. intangible (Garcia-Macia et al., 2017), durable vs. non-durable (Rampini, 2019), new vs. used (Lanteri and Rampini, 2023a), clean vs. dirty (Lanteri and Rampini, 2023b), and rival vs. non-rival (Crouzet et al., 2022).

financial markets and economic growth (see, e.g., Aghion, Howitt and Levine, 2018). We contribute by studying how financial frictions distort firms' joint decisions between investment and innovation and by quantifying the aggregate effects of the resulting distortions.

Road Map The rest of our paper is organized as follows. Section 2 elaborates on the established firms on which we focus our analysis. Section 3 documents the pecking order of firm growth in the data. Section 4 develops the model and Section 5 describes how the model generates the pecking order. Section 6 calibrates the key parameters of the model and shows that the model matches a number of untargeted statistics in the data. Section 7 uses the calibrated model to quantify the causal effect of financial frictions on the pecking order. Section 8 uses the model to quantify the aggregate costs of financial frictions. Section 9 studies the welfare effects of innovation and investment subsidies. Section 10 concludes.

2 Which Firms Are We Thinking About?

The majority of firms in the economy pursue little to no innovation and their optimal scale is very small, perhaps because they are filling local demand for nontradables or for other non-pecuniary reasons (see Hurst and Pugsley 2011). We exclude these firms from our analysis and instead focus on *innovative firms* whose decisions may meaningfully contribute to aggregate productivity.

We conceptualize the lifecycle of these innovative firms in two phases. In the *initial phase*, the firm innovates in order to create its first "scalable idea," i.e. an idea that requires a meaningful capital investment to successfully bring to market. These firms are innovation-intensive because they do not yet have a project into which they can devote meaningful investment. This view is consistent with the empirical evidence showing that the smallest and youngest firms in the economy are highly innovation-intensive (see, e.g., Akcigit and Kerr, 2018).[3] We also omit this phase from our analysis by modeling firms once they have successfully created their first scalable idea.

[3]These firms' innovation intensity will also be decreasing in their size to the extent that their size is determined by non-scalable products generating sales, again consistent with Akcigit and Kerr (2018). These firms will also rely heavily on equity finance since they have little capital to use as collateral, consistent with the role of venture capital and private equity in this market.

Once a firm creates and implements its first scalable idea, it enters the *established phase*. We focus on this phase because it is where the central tradeoff in our paper arises: how much should the firm scale up its existing idea through investment, and how much should it devote to generating a new idea through innovation? Our empirical evidence on the pecking order of firm growth guides the model we develop to study this tradeoff.

The empirical Compustat sample is a further subset of these established firms because inclusion in Compustat requires publicly traded debt or equity. This selection implies that the sample skews toward older and larger firms than the broader universe. We address this issue by including the full universe of established firms in the model and explicitly accounting for selection into Compustat.

3 Motivating Evidence

We document our pecking order of firm growth and argue that it is driven, at least in part, by financial frictions.

3.1 Data Description

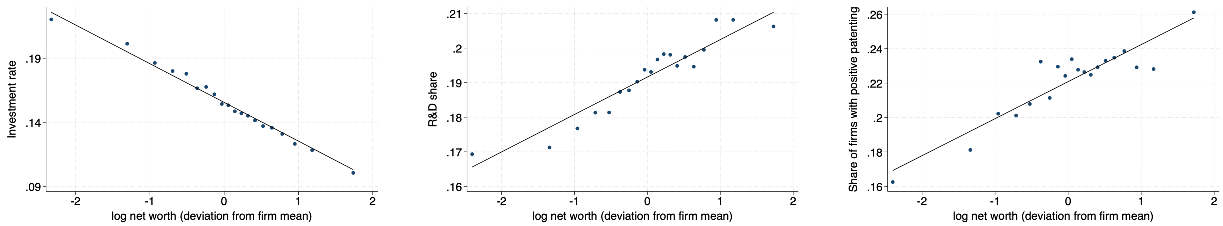
Our main analysis uses annual firm-level data from Compustat from 1975 to 2018. These data contain a long panel of firms' investment expenditures, R&D expenditures, and financial positions, allowing us to measure our key variables of interest. To our knowledge, Compustat is the only U.S. dataset with these features.

Our main outcomes of interest are firms' investment and innovation. We measure the investment rate as the ratio of capital expenditures to the lagged value of plant, property, and equipment. Innovation is more difficult to measure, so we proxy for it in two ways. First, we proxy for the inputs into the innovation process using R&D expenditures. Second, we proxy for the outputs of the innovation process using approved patents collected from the U.S. Patent and Trademark Office by Kogan et al. (2017). While neither proxy fully captures innovation decisions, together they are informative about firms' innovative activity.

We study how these outcomes vary with firms' financial positions to understand the effects of financial frictions. Our main measure of financial position is net worth, which is the value

Figure 1: The Pecking Order of Firm Growth

(a) Investment rates (b) R&D share (c) Patent activity



Notes: Binned scatter plots of investment rates, the R&D share, and the share of firms with positive patenting by the log of firm net worth. All variables are demeaned at the firm level. In order to make the units of the outcome variables more interpretable, we add back in the unconditional mean across all firms. For variable definitions and sample selection, see Appendix A.

of plant, property, and equipment, plus cash and short-term investments, minus total debt. We focus on net worth because it is the key state variable that determines the shadow price of external finance in our model. For our baseline analysis, we exclude observations associated with large acquisitions in order to focus on dynamics occurring within the same firm (though we obtain similar results when including acquisitions). Appendix A describes the details of how we clean the data and presents descriptive statistics of our final sample.

3.2 The Pecking Order of Firm Growth

We illustrate the pecking order of firm growth using simple binned scatterplots of investment and innovation by net worth. We isolate within-firm variation by de-meaning all variables at the firm level, which is equivalent to using a firm fixed effect in a regression context. We condition on firms with at least twenty years of observations in order to precisely estimate the firm-level mean, but Appendix A shows our results also hold for the full sample of firms. In order to make the units of the outcome variables interpretable, we add back in their mean values across all firms for these plots.

Panel (a) of Figure 1 shows that firms' investment rate *decreases* as they accumulate net worth; investment rates exceed 0.2 when firms have their lowest levels of net worth but then fall below 0.1 as firms accumulate net worth.[4] This pattern is consistent with the notion

[4] A potential concern with this result is that the firm's capital stock is a component of net worth and is also the denominator of the investment rate. Of course, that fact does not necessarily imply a mechanical negative relationship between the two variables because investment, the numerator of the investment rate, is an endogenous choice. Nevertheless, Table 1 shows that firm-level investment rates are also decreasing in

that firms face a steep return to capital schedule when they have low net worth.

In contrast, panels (b) – (c) show that firms' innovation activity *increases* as firms accumulate net worth. In terms of innovation inputs, we focus on the *R&D share*: the share of total expansionary expenditures devoted to R&D, measured as R&D expenditures divided by the sum of R&D and investment expenditures. Panel (b) shows that the R&D share increases by 25% as firms accumulate net worth. Appendix A shows that other measures of R&D activity, such as R&D-to-sales or the share of firms with positive R&D expenditures, also increase with net worth.[5] In terms of innovation outputs, panel (c) shows that patenting activity also increases as firms accumulate net worth. In particular, firms are about 50% more likely per year to obtain a successful patent when they have high net worth than when they have low net worth. Appendix A shows that other measures of patenting activity, such as the number of new patents per employee or the market value of those patents, also increase with net worth.

Pecking Order by Size and Age Although net worth maps directly into the shadow price of external finance in our model, the corporate finance literature often proxies for that shadow price using other measures of size and age. We now show that the pecking order holds using these alternative proxies as well.

We summarize the pecking order by size using the regression

$$o_{jt} = \alpha_j + \gamma \log s_{jt} + \epsilon_{jt}, \tag{1}$$

where o_{jt} is the outcome of interest (investment rate, R&D share, or indicator for patenting), α_j is a firm fixed effect, s_{jt} is the measure of size, and ϵ_{jt} is a residual. The coefficient of interest is γ, which measures how the outcome of interest varies with the particular measure of size. We standardize each size variable $\log s_{jt}$ over the entire sample in order to make the units of the coefficient γ easier to interpret. We cluster standard errors at the firm level.

the firms' sales or employment, which have no mechanical relationship with their capital stock. In addition, Appendix A shows that the investment-to-sales ratio is decreasing in net worth.

[5] A potential concern is that R&D expenditures are under-reported in the data. We address this concern in Appendix A by only using observations after the firm reports its first positive R&D expenditure and therefore has presumably set up the accounting infrastructure to report R&D going forward. We find similar results in this subsample.

Table 1
The Pecking Order by Various Measures of Size

	(1) Investment rate	(2) R&D share	(3) Patent activity
(a) Log net worth			
$\hat{\gamma}$	-0.068	0.023	0.045
	(0.003)	(0.003)	(0.007)
N	45667	47016	48939
Adjusted R^2	0.260	0.853	0.638
(b) Log capital			
$\hat{\gamma}$	-0.086	0.024	0.061
	(0.003)	(0.003)	(0.009)
N	49714	51293	53498
Adjusted R^2	0.268	0.848	0.631
(c) Log capital including intangibles			
$\hat{\gamma}$	-0.088	0.037	0.044
	(0.003)	(0.004)	(0.009)
N	44052	44395	46101
Adjusted R^2	0.278	0.847	0.634
(d) Log employment			
$\hat{\gamma}$	-0.045	-0.001	0.104
	(0.005)	(0.005)	(0.011)
N	44618	45682	47722
Adjusted R^2	0.205	0.846	0.634
(e) Log sales			
$\hat{\gamma}$	-0.059	0.017	0.090
	(0.004)	(0.004)	(0.010)
N	49704	51858	54480
Adjusted R^2	0.215	0.846	0.633

Notes: Results from estimating the regression $o_{jt} = \alpha_j + \gamma \log s_{jt} + \epsilon_{jt}$, where o_{jt} is the outcome of interest (investment rate, R&D share, or an indicator for positive patenting); s_{jt} is the measure of size (net worth, capital, capital including intangibles, sales, employment); and α_j is a firm fixed effect. We standardize the size measures $\log s_{jt}$ over the entire sample. Standard errors, reported in parentheses, are clustered at the firm level. The variable "capital including intangibles" is from Peters and Taylor (2017) and is measured by incorporating both the firm's past investment and R&D expenditures. For variable definitions and sample selection, see Appendix A.

The first row of Table 1 estimates the regression (1) in which s_{jt} is measured using net worth in order to quantify the magnitudes and statistical significance of the bin-scatters. Column (1) shows that having net worth one standard deviation higher than its mean lowers the firm's investment rate by nearly 50% relative to its mean. Columns (2) – (3) quantify the effect of net worth on our two proxies of innovation activity; for example, having net worth one standard deviation above its mean increases the R&D share by about 12% relative to its mean. All of these effects are statistically significant.

The remaining rows of Table 1 show that these patterns hold for other measures of size. The second row measures size using physical capital, i.e. plant, property, and equipment, while the third row uses the sum of physical and intangible capital from Peters and Taylor (2017). The fourth and fifth rows proxy for size using employment or sales. Net worth and these various measures of size are correlated in both the data and our model, so it is natural that the magnitudes of the pecking order are similar for all of these measures.

We summarize the pecking order by firm age using the regression

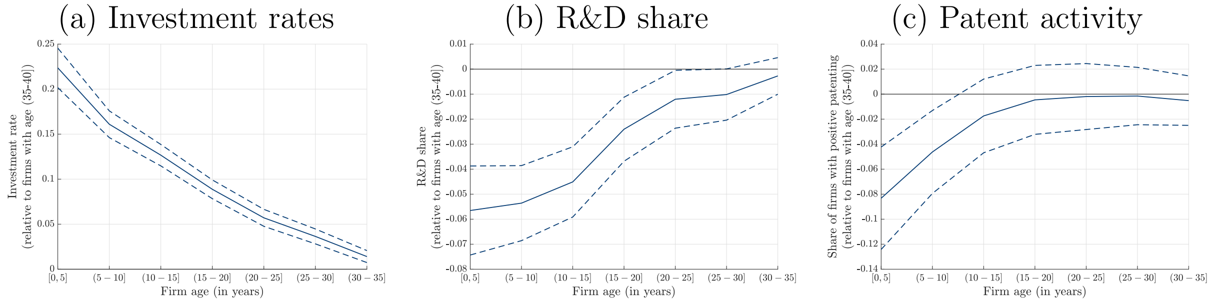
$$o_{jt} = \alpha_j + \sum_{s \in \mathcal{S}} \gamma_s \text{age}_{sjt} + \epsilon_{jt}, \tag{2}$$

where age_{sjt} is a dummy variable if the firm's age since incorporation (not IPO) falls in the bin $s \in \mathcal{S} \equiv \{[0, 5], (5, 10], (10, 15], (15, 20], (20, 25], (25, 30], (30, 35]\}$. We estimate the regression for firms with age up to 40 years—above which the number of observations per bin becomes too small—so the omitted group corresponds to the age range $(35, 40]$.

Figure 2 shows that firms are more investment-intensive when they are young, but become more innovation-intensive as they age. This finding is consistent with the idea that firms are more likely to be financially constrained when they are young.

Multivariate Analysis Of course, net worth, size, and age are all correlated, but Appendix Table A.4 shows that net worth remains a key determinant of the pecking order even after controlling for size and age dummies. This finding is consistent with our model, in which net worth is the key state variable determining the firm's cost of external finance. Appendix Table A.4 also shows that the pecking order by net worth is robust to controlling

FIGURE 2: The Pecking Order by Age



Notes: Results from estimating the regression $o_{jt} = \alpha_j + \sum_{s \in \mathcal{S}} \gamma_s \text{age}_{sjt} + \varepsilon_{jt}$, where o_{jt} is the outcome of interest (investment rate, R&D share, or an indicator for positive patenting); age_{sjt} is a dummy variable that takes the value of 1 if the firm's age of incorporation in period t is in group s and zero otherwise; and α_j is a firm fixed effect. We consider the following age groups:
$\mathcal{S} \equiv \{[0,5], (5,10], (10,15], (15,20], (20,25], (25,30], (30,35]\}$. We estimate the regression for firms with age up to 40 years, so the omitted group corresponds to age $(35, 40]$. Standard errors are clustered at the firm level and dashed lines correspond to 90% error bands. Firms' age since incorporation is obtained from Datastream. For other variable definitions and sample selection, see Appendix A.

for cash holdings. This result addresses the concern that our results are driven by a special role for cash that is absent from our model (in which cash is equivalent to negative debt).[6]

3.3 Suggestive Evidence About Financial Frictions

While the results so far are consistent with financial frictions shaping the pecking order, we do not have exogenous variation in net worth to isolate their causal effect. We therefore rely on the model to quantify the role of financial frictions. In this subsection, we present additional suggestive evidence linking the pecking order to financial frictions in order to further motivate the model we develop.

Financial Shocks First, we show that firms exposed to positive financial shocks, which relax their financial constraints, tilt the composition of spending away from investment and toward innovation. This result is consistent with our model because financial constraints delay firms' shift to innovation. We exploit cross-sectional heterogeneity in firms' exposure to idiosyncratic bank shocks through their pre-existing lending relationships, following a

[6] Falato et al. (2022) show that firms with higher intangible capital tend to have higher cash ratios, a pattern they interpret as reflecting the limited pledgeability of intangible assets. Relatedly, Begenau and Palazzo (2021) show that the rise in cash ratios among U.S. public firms is concentrated in R&D-intensive firms, especially among R&D-intensive new lists that go public with progressively higher cash-to-assets.

strategy in the spirit of Chodorow-Reich (2014). We obtain firm-bank relationships from Dealscan, which contains information on the firms in our Compustat sample that access the syndicated loan market (for details on these data and the structure of the market, see Chodorow-Reich, 2014). We combine these relationships with idiosyncratic shocks to banks' credit supply from Ottonello and Song (2025)'s "financial shocks" dataset. These data proxy for changes in banks' lending capacity using high-frequency stock-price changes in a narrow window around their earnings announcements.

Using these data, we construct the firm-specific financial shocks in two steps. First, we define the high-frequency firm–bank shock $\epsilon^F_{jit} \equiv \theta_{jit}\, \Delta p^F_{it}$, where Δp^F_{it} is the high-frequency change in the log stock price of bank i around its earnings announcement in quarter t, and θ_{jit} is an indicator if bank intermediary i was a lead arranger in firm j's most recent syndicated loan prior to period t. Second, we time aggregate these shocks across intermediaries and quarters and standardize the resulting firm-quarter aggregate ε^F_{jt} (see Appendix A.1 for details). Using these, we define the firm-level financial shock as $v_{jt} \equiv \rho_t\, \varepsilon^F_{jt}$, where ρ_t is an indicator for the Great Financial Crisis (2008Q1–2009Q2).[7] A positive shock corresponds to an increase in credit supply and therefore to a relaxation of the firm's financial constraints. We merge these shocks into quarterly Compustat to study their effects on investment and innovation.[8]

We estimate the effects of these shocks using

$$y_{jt+h} = \alpha_{jh} + \alpha_{sth} + \beta_h v_{jt} + \gamma_h v_{jt} x_{jt-1} + \delta'_h Z_{jt-1} + \varepsilon_{jth}, \tag{3}$$

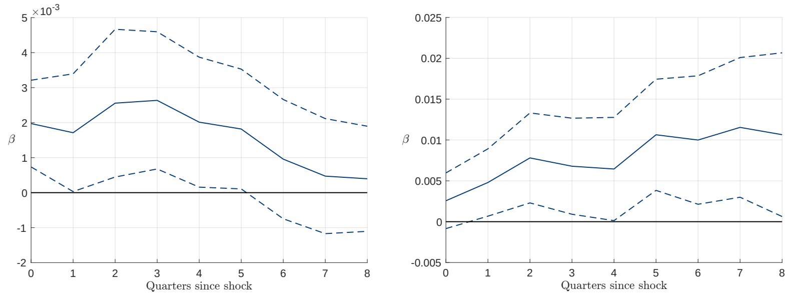
where y_{jt+h} is a firm-level outcome in period $t+h$; x_{jt-1} is an indicator if firm j's leverage is above its firm-specific mean in period $t-1$; α_{jh} and α_{sth} denote firm and sector-by-time fixed effects, respectively; and Z_{jt-1} is a vector of controls. Following Ottonello and Winberry (2020), we include sales growth, size, current assets as a share of total assets, firm-

[7] We condition on the financial crisis because bank-level shocks tend to affect firms primarily during periods of credit market disruption, possibly because it is difficult for firms to find new lenders (see Chodorow-Reich, 2014; Ottonello and Song, 2025).

[8] We use the quarterly version of Compustat for this analysis given the high-frequency nature of the shock. We apply the same restrictions to the Compustat variables as in the baseline sample, as described in Appendix A.

FIGURE 3: The Effects of Financial Shocks

(a) R&D Share (b) Intangible Assets



Notes: This figure reports the dynamic effects of financial shocks on high-leverage firms' outcomes, obtained from estimating

$$y_{j,t+h} = \alpha_{jh} + \alpha_{sth} + \beta_h v_{jt} + \gamma_h v_{jt} x_{j,t-1} + \Gamma_h' Z_{j,t-1} + \varepsilon_{jth},$$

where y_{jt+h} is a firm-level outcome; v_{jt} is the firm-level financial shock (standardized); x_{jt-1} is a dummy variable if firm j's leverage is above its firm-specific mean in period $t-1$; α_{jh} and α_{sth} denote firm and sector-by-time fixed effects; and $Z_{j,t-1}$ is a vector of controls that includes sales growth, size, current assets as a share of total assets, firm-by-fiscal-quarter dummies, the log number of lenders in the firm's most recent syndicated loan, x_{jt-1}, and $\rho_t x_{jt-1}$. Each panel reports $\Gamma_h = \hat{\beta}_h + \hat{\gamma}_h$ for a different outcome y_{jt+h}: the R&D share and intangible capital. Dashed lines report 90% confidence bands based on standard errors two-way clustered by firm and quarter. For variable definitions and sample selection, see Appendix A.

by-fiscal-quarter dummies, the log number of lenders in the firm's most recent syndicated loan, and x_{jt-1} and $\rho_t x_{jt-1}$. The coefficient of interest $\Gamma_h \equiv \beta_h + \gamma_h$ measures the effect of financial shocks on highly leveraged firms. We focus on highly leveraged firms because the literature shows that they are more sensitive to the lending capacity of the banks in their lending relationships (e.g., Berton et al., 2018; De Jonghe et al., 2020; Kalemli-Özcan, Laeven and Moreno, 2022). We estimate regression (3) over 1999–2020 (when financial shocks are available) on firms with an outstanding syndicated loan whose most recent deal includes a sample intermediary, and cluster standard errors by firm and quarter. For more details on the data and variables used in the analysis, see Appendix A.1.

Figure 3 reports the estimated effects of financial shocks, Γ_h, across horizons h. As a validation of the shock, Appendix A shows that a one-standard-deviation financial shock has a persistent effect on debt and external finance, peaking at 0.5 and 0.8 percentage points of assets two years after the shock. Our main result is in panel (a) of Figure 3, which shows that the R&D share rises in the quarters following a positive financial shock, equivalent to about a 0.8% increase relative to its mean—implying an elasticity of one to two with respect to the additional financing. Given the limitations of quarterly R&D reporting, Panel (b) shows that the book value of intangible assets increases by 1% following a positive financial shock. This increase is more than twice as large as the response of physical capital, which we also report in Appendix A. To the extent that intangible capital is more closely related to innovation activity, this result provides further evidence that firms tilt toward innovation after a relaxation of financial constraints.

Other Pieces of Evidence Appendix A presents two additional pieces of evidence suggesting that financial frictions matter for the pecking order. First, we provide illustrative examples of firm managers discussing the role of financial frictions in the mix of investment and innovation from earnings calls, collected from `NL Analytics`. Second, we show that the pecking order tends to be steeper in sectors with less pledgeable assets and, presumably, tighter financial constraints.

Robustness Appendix A.2 reports several additional robustness checks.

(i) *Other measures of innovation.* Appendix Figure A.3 shows that our baseline binscatter plots are similar using five other measures of innovation inputs: the ratio of R&D expenditures to sales, the share of firms with positive R&D, the R&D share for firms that have reported positive R&D in the past, the patents-to-employees ratio, and the total market value of those new patents granted in a given year, which is a measure of patent quality.

(ii) *Sources of variation.* Appendix Table A.2 shows that the pecking order is robust to alternative sources of variation in the data, such as including time fixed effects to capture trend changes in the composition of investment and innovation.

(iii) *Sample.* Appendix Table A.3 shows that the pecking order is also robust when using different samples of firms, such as all firms in the data or further conditioning only on Akcigit and Kerr (2018)'s "continuously innovative firms" that have conducted positive R&D or patenting activity at some point over the last five years.

4 Model

We now develop our model to study the extent to which financial frictions can account for the empirical evidence presented above and assess their aggregate implications. We specify the model to capture two salient differences between capital and ideas that shape the tradeoff between investment and innovation. First, there are *technological* differences between capital and ideas that determine their physical returns. Second, there are differences in *tangibility* that make capital easier to collateralize in external borrowing.

4.1 Environment

The model is set in discrete time and there is no aggregate uncertainty.

Technology At the beginning of each period t, there is a fixed mass of incumbent firms, indexed by j, that produce an undifferentiated good $y_{jt} = A_t z_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu}$. Here, A_t is an aggregate productivity shifter, z_{jt} is idiosyncratic productivity (pre-determined by past innovation decisions), k_{jt} is the firm's capital stock (pre-determined by past investment decisions), and ℓ_{jt} is the quantity of labor (hired in a frictionless spot market at real wage w_t). The production function features decreasing returns, $\alpha + \nu < 1$, which generate the profits to incentivize innovation efforts. The aggregate productivity shifter grows exogenously at rate g_A such that $A_t = (1 + g_A)^t$.

After production, an i.i.d. exit shock is realized such that firm j is forced to exit the economy with probability π_d. The exit shocks ensure that firms do not outgrow their financial frictions in the long run.[9] Upon exit, firms pay back their outstanding debt and transfer their remaining capital back to the household.

Firms that do not receive the exit shock choose investment and innovation to influence the evolution of their capital stock and idiosyncratic productivity going into the next period. Investment is standard: x_{jt} units of the final good yield $k_{jt+1} = (1-\delta)k_{jt} + x_{jt}$ units of capital

[9] We could endogenize the exit decision by assuming there is a fixed operating cost each period that the firm is in operation, as in Hopenhayn (1992). However, the simplest version of this extension would predict that firms' exit rates fall sharply in size and age, counterfactual to the data. One can view our exogenous exit shocks as a "disaster shock" to the firm's productivity or capital values which endogenously leads the firm to exit, even if the firm is old or large.

in the next period. Innovation is more involved: if a firm chooses innovation intensity i_{jt}, it has probability $\eta(i_{jt})$ of realizing a successful innovation. We parameterize

$$\eta(i_{jt}) = 1 - \frac{1}{\left(1 + \frac{i_{jt}}{\eta_0}\right)^{\eta_1}}, \tag{4}$$

where $\eta_0 \geq 0$ and $\eta_1 \geq 0$. This functional form is increasing, concave, and bounded between 0 and 1. In addition, $\eta'(0)$ is finite, allowing the model to generate inaction in innovation, as in the data. A successful innovation permanently raises the firm's log-productivity by Δ:

$$\log z_{jt+1} = \begin{Bmatrix} \log z_{jt} + \Delta - \phi \log Z_t \text{ with probability } \eta\left(i_{jt}\right) \\ \log z_{jt} - \phi \log Z_t \text{ with probability } 1 - \eta\left(i_{jt}\right) \end{Bmatrix}, \tag{5}$$

where $Z_t = \int z_{jt} dj$ is average productivity and $\phi \geq 0$. The drift term $-\phi \log Z_t$ is related to intertemporal knowledge spillovers, which we explain below.

In order to achieve innovation intensity i_{jt}, the firm must spend $\widetilde{A}_t \left(z_{jt}/Z_t\right)^{\frac{1}{1-\alpha-\nu}} i_{jt}$ units of output, where $\widetilde{A}_t = \left(A_t Z_t\right)^{\frac{1}{1-\alpha}}$.[10] This cost function satisfies two natural requirements. First, the term $\widetilde{A}_t$ grows with the economy so that firms do not outgrow innovation costs over time. Second, the term $\left(z_{jt}/Z_t\right)^{\frac{1}{1-\alpha-\nu}}$ implies that all financially unconstrained firms have the same growth rate, a property known as Gibrat's law. This property provides a useful benchmark for unconstrained firms; however, constrained firms grow faster than unconstrained firms because they have a higher marginal product of capital. Firms cannot sell their existing ideas, i.e. innovation intensity must be non-negative $i_{jt} \geq 0$.[11]

Financial Frictions Firms have two sources of finance for their investment and innovation expenditures. First, firms can issue new debt with face value b_{jt+1} that must be repaid in period $t+1$. Firms do not default on their debt, so they receive $\frac{b_{jt+1}}{1+r_t}$ units of output in

[10] We denominate the costs of innovation in units of output to make them symmetric with the costs of investment. Implicitly, this assumes that both capital and labor are used to innovate.

[11] In principle, financially constrained firms may have an incentive to sell their ideas in order to finance investment. In practice, the "market for ideas" — licensing arrangements, patent sales, mergers and acquisitions, etc. — is rife with frictions. We view our assumption that $i_{jt} \geq 0$ as the limit in which those frictions are sufficiently large to prevent trade in the market for ideas altogether. These frictions allow the model to generate inaction in innovation rates, which is common in the data.

period t, where r_t is the risk-free interest rate. Borrowing is subject to the constraint $b_{jt+1} \leq \theta_t(z_{jt}, i_{jt}, k_{jt+1})$, which allows us to flexibly capture different degrees of collateralizability across old ideas z_{jt}, new ideas i_{jt}, and capital k_{jt+1}.

Second, firms can finance expenditures using internal resources, but we assume that they cannot issue new equity. Hence, dividend payments must satisfy

$$d_{jt} = A_t z_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu} - w_t \ell_{jt} + (1-\delta) k_{jt} - b_{jt} - k_{jt+1} - \widetilde{A}_t \left(\frac{z_{jt}}{Z_t}\right)^{\frac{1}{1-\alpha-\nu}} i_{jt} + \frac{b_{jt+1}}{1+r_t} \geq 0.$$

As is common in the macroeconomics literature (see, e.g., Khan and Thomas 2013 and Ottonello and Winberry 2020), we abstract from equity issuance for parsimony. Modeling equity issuance would require incorporating additional financing frictions (see, e.g., Guo et al. 2025), significantly complicating the model. Such an extension could affect our mechanism by expanding firms' access to external finance and allowing ideas to support financing through their effect on firm value. Below, we show that our results are robust to extensions that capture these two forces.

Entry Each period, there is a fixed flow π_d of new entrants with $b_{jt+1} = 0$, $z_{jt+1} = Z_{t+1}$, and $k_{jt+1} = k_0 \widetilde{A}_t$. This simple entry process captures the notion that new entrants are rich in ideas but poor in capital: their productivity equals average productivity, reflecting imitation of incumbents, while k_0 is below their optimal scale.[12] This assumption is consistent with empirical evidence on scale-dependent growth from, e.g., Haltiwanger, Jarmin and Miranda (2013). We scale initial capital by $\widetilde{A}_t$ to ensure it grows with the rest of the economy. This entry process generates positive innovation spillovers because incumbents' innovations raise average productivity Z_{t+1} and, therefore, the productivity of new entrants.[13]

Household There is a representative household with the utility function $\sum_{t=0}^{\infty} \beta^t (\log C_t - \chi L_t)$, where C_t is aggregate consumption and L_t is aggregate labor supply. Since there is no ag-

[12]One can view these initial conditions as a simple representation of the outcomes of a rich process of firm dynamics during the initial phase described in Section 2.

[13]Note that the term $-\phi \log Z_t$ in the evolution of productivity (5) also controls the strength of these intertemporal spillovers onto entrants.

gregate uncertainty, firms discount profits using the risk-free interest rate

$$\frac{1}{1+r_t} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{-1}. \tag{6}$$

In addition, the real wage is proportional to aggregate consumption:

$$w_t = \chi C_t. \tag{7}$$

4.2 Equilibrium

Firms' choice of labor demand each period is static, generating operating profits $\pi_t(z_{jt}, k_{jt}) = \max_{\ell_{jt}} A_t z_{jt} k_{jt}^{\alpha} \ell_{jt}^{\nu} - w_t \ell_{jt}$. Their other choices are dynamic, so it is convenient to formulate the problem recursively. The individual state variables are the firm's idiosyncratic productivity z_{jt} and net worth $n_{jt} = \pi_t(z_{jt}, k_{jt}) + (1-\delta)k_{jt} - b_{jt}$; we absorb the aggregate state into time subscripts. Exiting firms set $k_{jt+1} = b_{jt+1} = i_{jt} = 0$, while continuing firms' decisions are characterized by the Bellman equation

$$v_t^{\text{cont}}(z,n) = \max_{k',i,b'} n - k' - \widetilde{A}_t \left(z/Z_t\right)^{\frac{1}{1-\alpha-\nu}} i + \frac{b'}{1+r_t} + \frac{1}{1+r_t} \mathbb{E}_t \left[v_{t+1}(z', n') \right] \tag{8}$$
$$\text{s.t. } d \geq 0 \text{ and } b' \leq \theta_t(z, i, k'),$$

where $\mathbb{E}_t \left[v_{t+1}(z', n') \right]$ integrates over the next period's exit shock and innovation success. The implied decision rules induce a law of motion for the distribution of firms, $\Phi_{t+1}(z,n) = T(\Phi_t; k'(\cdot), i(\cdot), b'(\cdot))(z,n)$.

A *competitive equilibrium* is a sequence of value functions $v_t(z,n)$; policies $k_t'(z,n)$, $i_t(z,n)$, and $b_t'(z,n)$; distribution of firms $\Phi_t(z,n)$; prices w_t and r_t; and average productivity Z_t such that (i) firms optimize and the associated policy functions solve the Bellman equation (8); (ii) the evolution of $\Phi_t(z,n)$ is consistent with firm decisions and the entry/exit process; (iii) prices are given by (6) and (7) with $C_t = \int \left(y_{jt} - (k_{jt+1} - (1-\delta)k_{jt}) - \widetilde{A}_t \left(z_{jt}/Z_t\right)^{\frac{1}{1-\alpha-\nu}} i_{jt} \right) dj$; and (iv) average productivity Z_t is consistent with firms' innovation decisions.

Aggregate Innovation Index The economy is nonstationary due to both exogenous and endogenous sources of growth. Appendix B shows that all quantity variables and the real wage scale with $\widetilde{A}_t = (A_t Z_t)^{\frac{1}{1-\alpha}}$, whose growth rate is

$$1 + g_t = [(1 + g_A)(1 + g_{Zt})]^{\frac{1}{1-\alpha}}, \tag{9}$$

where $1 + g_{Zt} = Z_{t+1}/Z_t$ is the growth rate of average productivity.

Firms' innovation decisions endogenously influence g_{Zt} and therefore the aggregate growth rate g_t. Integrating across firms, Appendix B shows that we can write the consistency condition for Z_t as

$$1 + g_{Zt} = Z_t^{-\phi} \mathcal{I}_t, \text{ where } \mathcal{I}_t = \int \frac{z_{jt}}{Z_t} \left[1 + \eta(i_{jt})(e^{\Delta} - 1)\right] dj. \tag{10}$$

We refer to $\mathcal{I}_t$ as the *aggregate innovation index* because it summarizes the impact of individual firms' innovation decisions on aggregate growth. Writing the equilibrium mapping as in (10) is conceptually useful because it separates the effect of firms' individual decisions on the aggregate innovation index $\mathcal{I}_t$ from the effect of $\mathcal{I}_t$ on aggregate productivity growth. We are able to discipline the first component using micro data, but there is much less discipline on the parameter ϕ which governs the second component.

Writing (10) as $Z_{t+1} = Z_t^{1-\phi} \mathcal{I}_t$ shows that $1-\phi$ is the elasticity of future productivity with respect to current productivity, i.e., the *intertemporal knowledge spillovers* in the language of Atkeson and Burstein (2019). The behavior of the balanced growth path (BGP) depends discontinuously on the value of ϕ; if $\phi = 0$, then $Z_{t+1} = Z_t \mathcal{I}_t$, so that along a BGP the growth rate of productivity satisfies $1 + g_Z = \mathcal{I}$ and is therefore endogenous. By contrast, if $\phi > 0$, then along a BGP productivity converges to the constant level $Z = \mathcal{I}^{\frac{1}{\phi}}$ and $g_Z = 0$ (although there will still be exogenous growth if $g_A > 0$). However, despite this discontinuity, the transition path in our counterfactual experiments is continuous in ϕ.

Our strategy is to set $\phi = 0$ as our baseline and then present sensitivity analysis for alternative values of $\phi > 0$. Given our calibration strategy in Section 6, firms' detrended decision rules along the initial BGP are independent of the value of ϕ.[14] However, the effects

[14]For any value of ϕ, we choose g_A so that the aggregate growth rate $g^* = 0.02$ in the initial BGP. In this

of removing financial frictions in our counterfactuals do depend on the value of ϕ; we find these results are qualitatively robust as we increase ϕ provided that ϕ remains within the range usually considered by the literature.

5 The Pecking Order of Firm Growth

We now show how financial frictions generate the pecking order of firm growth in the model.

5.1 Characterizing Decision Rules

We illustrate the model's pecking order by plotting firms' decision rules for investment and innovation along the BGP. A key object for characterizing these decisions is the marginal value of funds inside the firm, $\frac{\partial v_t(z,n)}{\partial n}$. This object is important because it represents the opportunity cost of instead spending the marginal unit of net worth on investment or innovation, and therefore equals the marginal cost of spending.

Financial frictions raise the marginal cost of spending by increasing the marginal value of funds inside the firm. In particular, Appendix B shows that value is $\frac{\partial v_t(z,n)}{\partial n} = 1 + \lambda_t(z,n)$, where $\lambda_t(z,n)$ is the Lagrange multiplier on the non-negativity constraint on dividends. At the optimum, this multiplier equals the expected value of the multipliers on the borrowing constraint $\mu_t(z,n)$ in all possible current and future states. We therefore refer to the multiplier $\lambda_t(z,n)$ as the *financial wedge* because it summarizes how all financial frictions together affect the marginal cost of spending.

***Proposition* 1.** *Consider a firm in period t that will continue operations in $t+1$, has productivity z, and has net worth n. Then there exist two functions $\overline{n}_t(z)$ and $\underline{n}_t(z,n)$ that partition the individual state space such that*

(i) ***Financially unconstrained****: If $n \geq \overline{n}_t(z)$, then the financial wedge $\lambda_t(z,n) = 0$. In this region, the capital accumulation $k_t^*(z)$, innovation $i_t^*(z)$, and borrowing $b_t^*(z)$ policies are independent of net worth.*

case, ϕ only affects firms' detrended decision rules through the implied drift in idiosyncratic productivity z. In logs, this drift is equal to $-\phi \log Z - \log(1+g_Z) = -\log \mathcal{I}$. However, the value of $\mathcal{I}$ in (10) itself only depends on the detrended decision rules and is therefore the same for all values of ϕ.

(ii) ***Currently constrained****: If $n \leq \underline{n}_t(z,n)$, then both the collateral constraint binds $b' = \theta_t(z,i,k')$ and the financial wedge is positive $\lambda_t(z,n) > 0$.*

(iii) ***Potentially constrained****: If $n \in (\underline{n}_t(z,n), \overline{n}_t(z))$, the collateral constraint is not currently binding $b' < \theta_t(z,i,k')$ but the financial wedge is positive $\lambda_t(z,n) > 0$.*

In all of these cases, the optimal choices for external financing $b'_t(z,n)$, investment $k'_t(z,n)$, and innovation $i_t(z,n)$ satisfy the first-order conditions

$$k' + \widetilde{A}_t \left(z/Z_t\right)^{\frac{1}{1-\alpha-\nu}} i = n + \frac{b'}{1+r_t} \text{ if } \lambda_t(z,n) > 0; \text{ otherwise, } b'_t(z,n) = b^*_t(z), \tag{11}$$

$$1 + \lambda_t(z,n) = \left\{ \begin{array}{l} \frac{1}{1+r_t}\mathbb{E}_t\left[(\pi_{2,t+1}(z',k') + 1 - \delta) \times (1 + (1-\pi_d)\lambda_{t+1}(z',n'))\right] \\ \qquad + \mu_t(z,n)\theta_{3,t}(z,i,k') \end{array} \right\} \tag{12}$$

$$1 + \lambda_t(z,n) \geq \frac{1}{\widetilde{A}_t \left(z/Z_t\right)^{\frac{1}{1-\alpha-\nu}}} \left\{ \begin{array}{l} \frac{\eta'(i)}{1+r_t}\left(\mathbb{E}_t[v_{t+1}(z',n'|\iota_{t+1}(z,n)=1] - \mathbb{E}_t[v_{t+1}(z',n'|\iota_{t+1}(z,n)=0)]\right) \\ \qquad + \mu_t(z,n)\theta_{2,t}(z,i,k') \end{array} \right\},$$

with equality if $i_t(z,n) > 0$. (13)

Proof. See Appendix B. ■

This proposition extends a similar characterization of decision rules in Khan and Thomas (2013)'s model without innovation. The first part of the proposition partitions the state space into three regions. *Financially unconstrained* firms have zero probability of facing a binding collateral constraint at any future date, which implies that their financial wedge is $\lambda_t(z,n) = 0$. Their decision rules are therefore independent of net worth n.[15] The remaining firms are affected by financial frictions in some way. *Currently constrained* firms face a binding borrowing constraint in the current period, which directly limits their ability to borrow. *Potentially constrained* firms do not face a binding constraint in the current period, but may be constrained in the future, which affects their current decisions.

The second part of the proposition characterizes the first-order conditions for these firms'

[15] A version of the Modigliani-Miller theorem holds for these firms in the sense that they are indifferent across any combination of external financing b' and internal financing d that leaves them financially unconstrained. Following Khan and Thomas (2013), we resolve this indeterminacy by requiring that firms pursue the "minimum savings policy," i.e., the largest level of b' that leaves them unconstrained with probability one (see Appendix B for details).

decisions. As discussed above, the marginal cost of spending on the left-hand side of (12) and (13) is the marginal value of funds inside the firm, $1 + \lambda_t(z, n)$. The marginal benefit of investment on the right-hand side of (12) consists of two terms: the expected marginal profitability of capital next period, weighted by the marginal value of funds in each state, and the marginal collateral benefit of capital. The marginal benefit of innovation on the right-hand side of (13) is the marginal increase in the success probability, per unit of innovation expenditure, times the sum of the increase in firm value from a successful innovation and the marginal collateral benefit of that innovation.

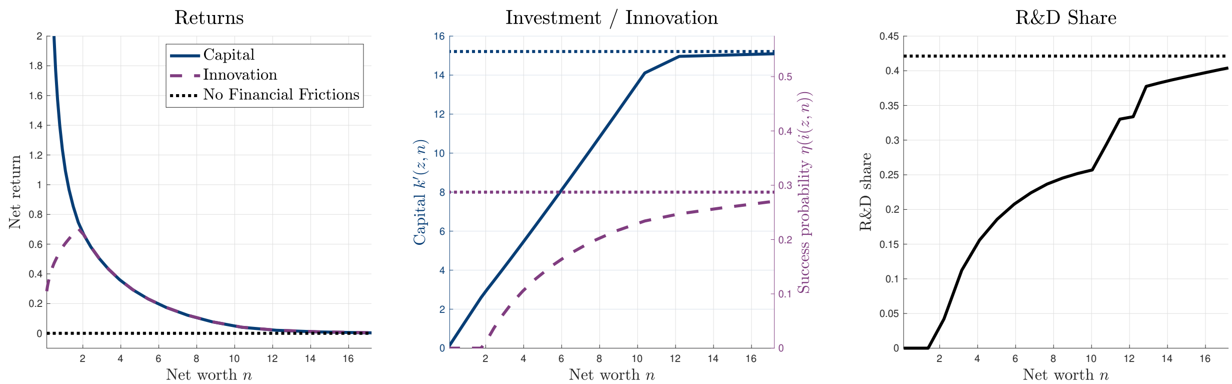
The first terms in (12) and (13) capture the technological differences between capital and ideas: capital raises future profits through the marginal product of capital, while innovation raises the probability of a successful idea. The second terms capture tangibility differences through the extent to which capital and ideas relax the borrowing constraint.

5.2 The Pecking Order in the Model

Figure 4 illustrates the model's pecking order by plotting firms' decision rules along the initial BGP as a function of net worth n (holding productivity z fixed for the sake of illustration). The left panel plots the net returns to investment and innovation, defined as the right-hand sides of the first-order conditions (12) and (13) minus 1. The middle panel plots capital expenditures $k'_t(z, n)$ on the left axis and innovation intensity $i_t(z, n)$ on the right axis. The right panel plots the R&D share, defined as in the data as innovation expenditures, $\widetilde{A}_t\,(z/Z_t)^{\frac{1}{1-\alpha-\nu}}\, i_t(z, n)$, divided by total investment and innovation expenditures, $\widetilde{A}_t\,(z/Z_t)^{\frac{1}{1-\alpha-\nu}}\, i_t(z, n) + k'_t(z, n) - (1-\delta)k$. The R&D share is a useful summary of the pecking order because it captures the firm's innovation intensity relative to its total expenditures on expansion (through both investment and innovation). We generate these plots using the calibrated parameters from Section 6, but the qualitative properties they illustrate hold over a wide range of the parameter space.

For the lowest levels of net worth, the firm does not innovate because the return to investment lies strictly above the return to innovation. In this region, the technological differences between capital and ideas imply that the technological return to investment is higher than the return to innovation. This occurs because the marginal profitability of

Figure 4: The Pecking Order of Firm Growth in the Model



Notes: Features of the firms' decision rules along the initial balanced growth path as a function of net worth n, holding the level of productivity z fixed. Left panel plots the net returns to investment or innovation, defined as the right-hand side of the Euler equations (12) and (13) minus 1. The middle panel plots capital expenditures $k_t'(z,n)$ (left axis) and innovation intensity $i_t(z,n)$ (right axis). The right panel plots the R&D share, defined as innovation expenditures divided by innovation plus investment expenditures. "No financial frictions" refers to the unconstrained policies $k^*(z)$ and $i^*(z)$ from Proposition 1.

capital on the right-hand side of (12) features an Inada condition, whereas the marginal success probability of innovation $\eta'(i)$ on the RHS of (13) does not. In addition, our baseline parameterization implies that capital is more tangible than ideas in the sense that it has a higher collateral benefit $\mu_t(z,n)\theta_{3,t}(z,i,k')$ than does innovation $\mu_t(z,n)\theta_{2,t}(z,i,k')$. In this region of the pecking order, the firm grows only by accumulating capital. As it does so, it drives down the return to investment while at the same time driving up the return to innovation, due to the complementarity between capital and ideas in production.

As the firm grows and increases its net worth, the returns to investment and innovation eventually intersect, so the firm begins innovating, $i_t(z,n) > 0$. Since the innovation first-order condition (13) now holds with equality, the net returns to investment and innovation are both equal to the financial wedge $\lambda_t(z,n)$. At this point, the R&D share gradually begins to rise from zero to its eventual unconstrained value. The R&D share is initially low because the return schedule for capital is steeper than for innovation, so more investment is required to keep the marginal returns to investment and innovation equalized. As the firm continues to grow, the return schedule for capital flattens, so relatively more R&D is required to equalize the marginal returns. Eventually, the financial wedge approaches zero and the firm's capital approaches its optimal scale. Once it reaches this region, the only way it can grow further is through the realization of a successful innovation.

Taken together, these three regions of the state space form the pecking order of firm growth in our model: firms are investment-intensive when they have low net worth but gradually shift toward innovation as they accumulate net worth. This pattern reflects the typical firm dynamics in the model for two reasons. First, firms enter the economy with a new idea but less capital than the optimal scale, $k < k_t^*(z)$, placing them in the first region of the pecking order. Second, incumbent firms that successfully generate a new idea similarly find themselves with a capital stock below their new optimal scale, again satisfying $k < k_t^*(z)$. These firms may therefore re-enter an earlier region of the pecking order and prioritize investment before innovating again.

Financial Frictions Create the Pecking Order Financial frictions are key to the model's pecking order because they determine how quickly firms can accumulate net worth and shift toward innovation. Figure 4 shows that, without financial frictions, the model would have no pecking order at all: firms would raise the external finance necessary to immediately reach their optimal scale, after which they would grow only through innovation. In this case, investment and innovation would become independent of net worth. Hence, the existence of the pecking order is a manifestation of financial frictions in our model.

6 Parameterization

We now calibrate the model in order to quantify the causal role of financial frictions in generating the pecking order.

6.1 Strategy for Disciplining Key Forces

The tangibility differences between capital and ideas are summarized by the borrowing capacity function $\theta_t(z, i, k')$. As a baseline, we assume that borrowing capacity is determined by the firm's capital, i.e. $\theta_t(z, i, k') = \theta k'$, where $0 \leq \theta \leq 1 - \delta$ is a parameter. This functional form, standard in the macroeconomics literature (e.g. Kiyotaki and Moore 1997), assumes that ideas are not collateralizable. Later, we show that the model continues to generate a pecking order even when ideas are collateralizable.

The technological return to investment is pinned down by the production technology and can therefore be disciplined in a standard way. The technological return to innovation—the idea arrival function $\eta(i)$ and resulting productivity improvement Δ—is more difficult to discipline because new ideas are difficult to measure in the data. The most common approach in the literature is to proxy for innovation output using patenting activity. A limitation of this approach, however, is that many innovations are not patented (see Adhami 2025).

We provide an alternative approach to disciplining the innovation technology using what firms reveal through their forward-looking investment decisions. Specifically, when a firm receives a successful innovation, it undergoes an investment spike—a large but short-lived surge in investment—as capital adjusts to the new level of productivity. The responsiveness of investment spikes to R&D expenditures is therefore informative about the innovation technology, without needing to rely on patenting activity to proxy for successful innovations.[16]

We implement this approach using the empirical relationship between investment spikes and R&D expenditures in our Compustat data. Following Cooper and Haltiwanger (2006), we define investment spikes as years in which a firm's investment rate exceeds 20%. We then estimate the linear probability model

$$\mathbb{1}\{\frac{x_{jt}}{k_{jt}} \geq 0.2\} = \alpha_j + \alpha_{st} + \sum_{h=1}^{H} \beta_h \left(\frac{\text{RD}_{jt-h}}{\tilde{y}_{jt-h}}\right) + \Gamma' X_{jt} + \epsilon_{jt}, \tag{14}$$

where $\frac{x_{jt}}{k_{jt}}$ denotes the investment rate of firm j in period t, $\frac{\text{RD}_{jt}}{\tilde{y}_{jt}}$ the R&D-to-sales ratio, α_j and α_{st} firm and time by 4-digit sector fixed effects, X_{jt} is a vector of firm-level controls, and ϵ_{jt} is a residual. Our coefficient of interest, β_1, measures how the probability of an investment spike is related to previous R&D expenditures. We set $H = 4$ for our baseline model and two-way cluster standard errors by firm and year.

The vector X_{jt} controls for two alternative sources of investment spikes that are unrelated to the innovation technology. First, we include the firm's current cash flow to control for

[16] This approach relies on the assumption that a successful innovation creates a discrete jump in productivity, reflecting the non-normal, discrete nature of innovation, which is a classic feature of growth models (e.g., Aghion and Howitt, 1992; Grossman and Helpman, 1991).

Table 2
R&D Expenditures Predict Investment Spikes

	(1)	(2)	(3)
$\frac{R\&D_{t-1}}{y_{t-1}}$	1.57	1.16	1.17
	(0.16)	(0.14)	(0.14)
Controls	No	Cash flows	Cash flows, years since the last spike, capital to labor ratio
Observations	48,293	48,293	48,293
Adj. R^2	0.280	0.310	0.312

Notes: Results from estimating $\mathbb{1}\{\frac{x_{jt}}{k_{jt}} \geq 0.2\} = \alpha_j + \alpha_{ts} + \sum_{h=1}^{4} \beta_h \left(\frac{\text{RD}_{jt-h}}{\tilde{y}_{jt-h}}\right) + \Gamma' X_{jt} + \epsilon_{jt}$, where $\frac{x_{jt}}{k_{jt}}$ denotes the investment rate of firm j in period t; $\frac{\text{RD}_{jt}}{\tilde{y}_{jt}}$ the R&D-to-sales ratio; α_j and α_{ts} firm and time by sector fixed effects; X_{jt} is a vector of firm-level controls; and ϵ_{jt} is a residual. Column (1) reports estimates for a specification without firm-level time-varying controls X_{jt}; Column (2) those that include cash flows ($\frac{\text{cf}_{jt}}{k_{jt}}$) as a control; and Column (3) those that also include the lumpy-investment controls (years since the last investment spike, years since spike$_{t-1}$, and the (lagged) standardized capital-employment ratio, $\frac{k_{jt-1}}{\ell_{jt-1}}$). To estimate the models reported in Columns (1) and (2), we restrict the sample to that with available observations in Column (3). For variable definitions and descriptive statistics, see Appendix A.

the possibility that past R&D predicts investment spikes because it raises internal funds and relaxes financial constraints, rather than because it predicts the arrival of a new idea.

Second, we control for the influence of non-convex capital adjustment costs, which may also generate investment spikes in the data but are absent from our model. We emphasize that the presence of such adjustment costs does not invalidate our approach because it does not assume that *all* investment spikes are generated by a new idea, only the component of spikes predicted by past R&D expenditures. Nevertheless, one may be concerned that non-convex adjustment costs may alter this conditional relationship. To address this concern, we include two proxies for the firm's likelihood of an investment spike: the time since its last investment spike and its standardized capital-to-labor ratio (which is informative if labor is more flexible and therefore better reflects current productivity z than the capital stock k).

Table 2 shows that R&D expenditures are a strong predictor of investment spikes. Column (1) reports the estimated coefficient β_1 from the linear probability model (14) without any additional controls X_{jt}. Column (2) shows that this estimate survives controlling for changes in cash flow. Quantitatively, the estimated coefficient implies that having last year's R&D-to-sales ratio one standard deviation above the mean raises the probability of an investment spike by around 7 percentage points, i.e. a 28% increase relative to its unconditional mean. Column (3) shows that the estimate also survives controlling for our proxies of non-convex adjustment costs, indicating that such costs do not affect the pass-through of R&D to investment spikes in the data. Appendix A presents additional analysis, such as using different measures of investment spikes, using different lags of R&D expenditures, and using additional control variables.

These results suggest a tight link between R&D expenditures and investment behavior, as predicted by our model. We therefore target the estimated coefficient β_1 in calibration. We use the estimate controlling for cash flows from column (2) in order to isolate the role of the innovation technology rather than financial constraints. We emphasize that our approach provides an alternative to the standard practice of using patenting activity to proxy for successful innovations; however, none of our qualitative results depends on using this approach over the usual one.

6.2 Calibration

We now calibrate the model in two steps. First, we fix a subset of parameters to match standard targets. Second, we choose the remaining parameters so that moments implied by the model's BGP match key features of the data.

Fixed Parameters Table 3 reports the parameters that we fix. We set the household's discount factor β to ensure that the real interest rate is 4% along the initial BGP. We set the labor elasticity in production ν to generate a labor income share of 55%, in line with recent estimates (e.g. Karabarbounis and Neiman 2014). Given this value, we then set the capital elasticity α so that the total elasticity of operating profits to variable inputs, $\frac{\alpha}{1-\nu} = 0.56$, which is close to the 0.59 value Cooper and Haltiwanger (2006) estimate. We assume $\pi_d = 8\%$ of firms exit per year, broadly consistent with exit rates both in the Business Dynamics Statistics (BDS) and in our Compustat sample.

For our baseline analysis, we set $\phi = 0$, which implies an elasticity of intertemporal knowledge spillovers of one. As described in Footnote 14, the detrended decision rules in the initial BGP, and therefore our calibration targets, are independent of the value of ϕ.

TABLE 3
FIXED PARAMETERS

Parameter	Description	Value
Household		
β	Discount factor	0.98
Firms		
ν	Output elasticity w.r.t labor	0.55
α	Output elasticity w.r.t capital	0.25
δ	Depreciation rate	0.08
π_d	Exit rate	0.08
Spillovers		
$1 - \phi$	Intertemporal knowledge spillovers	$1\ (\rightarrow \phi = 0)$

Notes: parameters chosen exogenously to match external targets.

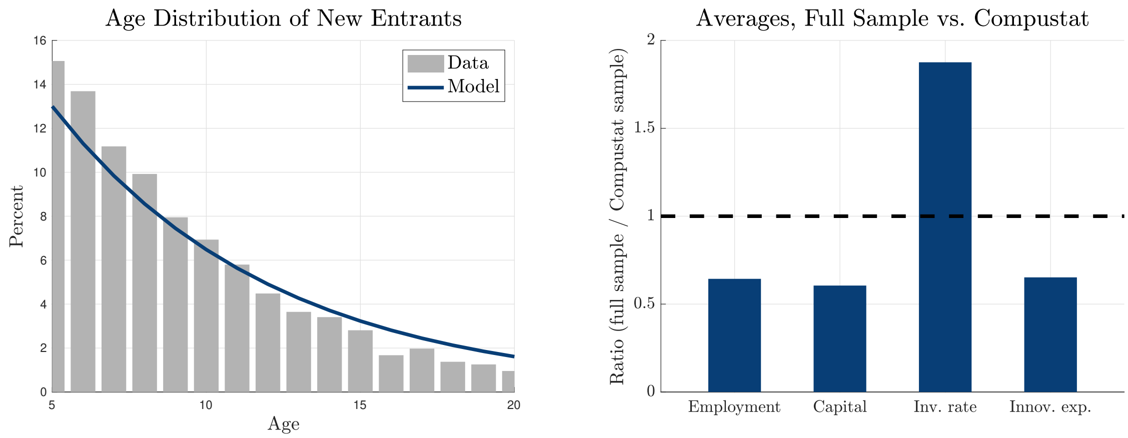
Modeling Selection Into Compustat We now turn to the parameters that we choose to match targets in the data. Most of these targets are drawn from our Compustat sample, which consists of publicly traded firms and is therefore not representative of the typical innovative firm in the economy, as discussed in Section 2. Of course, the decision to go public is a rich endogenous choice, involving multiple benefits—such as cheaper financing, better scalability, or diversified ownership—and multiple costs, such as underwriting costs, legal costs, or the loss of corporate control.

Fully modeling this decision is beyond the scope of the paper; instead, we capture selection into Compustat using a simple statistical model. Specifically, we construct an *artificial Compustat sample* from which we compute statistics that will be matched to Compustat data. All firms enter the economy outside of this artificial Compustat sample, and there is zero probability they enter it when their age a is below $\underline{a}$. For ages $a \geq \underline{a}$, there is probability ζ each period that the firm receives a shock upon which it enters the artificial Compustat sample and remain until they exit the economy. Hence, firm age upon entry into Compustat, a^{entry}, follows the distribution

$$\Pr\left(a^{\text{entry}} = a \,\middle|\, a^{\text{entry}} \geq \underline{a}\right) \; = \; \zeta \, (1 - \zeta)^{\, a - \underline{a}}. \tag{15}$$

We estimate this simple model of selection by matching (15) to the empirical distribution of firm age at their initial public offering (IPO). In the data, we compute the age at IPO as

Figure 5: Modeling Selection Into Compustat



Notes: left panel plots distribution of firm age of new entrants into Compustat, where entry corresponds to the IPO year (Compustat's `ipodate`) and age corresponds to age since incorporation (from Datastream, as described in Appendix A). In the model, we mirror sample selection into Compustat following the procedure in the main text. Right panel plots the average values of employment, capital, investment rate, and innovation expenditures in our model's full sample and the Compustat subsample.

the difference between the year of the IPO and the year of incorporation. We then restrict the sample to only include firms with $a^{\text{entry}} \geq \underline{a} = 5$ to exclude observations that may not be associated with a new firm.[17]

The left panel of Figure 5 shows that the empirical distribution of age at IPO is approximately geometric, consistent with our simple model. We estimate the selection parameter ζ to match the model-implied distribution (15) to the empirical one, yielding $\zeta = 0.13$. Given $\underline{a} = 5$, our model also matches the median age at IPO of 9 years reported by Ritter (2025).

Of course, the empirical Compustat sample may also be selected along other firm characteristics, such as size. Quantifying these other sources of selection is difficult because, as discussed in Section 2, our model excludes many small, local, and non-innovative firms which dominate publicly available data on non-Compustat firms. Instead, the right panel of Figure 5 compares the artificial Compustat sample to the full sample within the model. The selection procedure passes an intuitive reality check: firms in the artificial Compustat

[17] Loughran and Ritter (2004) argue that such observations are more likely to correspond to events such as divisional spinoffs, reincorporations in Delaware, or reverse LBOs. In a reverse LBO, a firm previously acquired in a debt-financed buyout is subsequently re-listed through a new IPO (see Kaplan and Strömberg, 2009; Cao and Lerner, 2009, for more details on these transactions).

Table 4
Fitted Parameters and Empirical Targets

Parameter	Description	Value	Target (all joint)	Data	Model
Innovation technology					
η_0	Success probability	0.08	Regression coefficient	1.16	1.12
η_1	Success probability	0.50	Mean R&D Share	0.46	0.39
Δ	Size of success	0.09	SD R&D Share	0.28	0.21
			Mean investment spike	0.37	0.33
Financial frictions					
θ	Collateral	0.35	Mean net leverage	0.16	0.17
Initial Capital					
k_0	Initial capital	$0.02 \times K^*$	Entrants' rel. employment (Davis-Haltiwanger)	0.10	0.10

Notes: left panel contains the parameters chosen to match the moments in the right table. "Success probability" refers to $\eta(i)$ from equation (4). "Regression coefficient" is the regression coefficient β_1 from Table 2 column (2). "R&D share" is computed as $\frac{RD_{jt}}{RD_{jt}+x_{jt}}$ where $RD_{jt} = \widetilde{A}_t(z_{jt}/Z_t)^{\frac{1}{1-\alpha-\nu}} i_{jt}$. We condition on observations for which $RD_{jt} > 0$ in the model and the data. Leverage is computed as $b_{jt}/(k_{jt} - \min\{b_{jt}, 0\})$, corresponding to net leverage in the data. "Entrants' rel. employment" is the employment of new entrants relative to average employment in the economy. All statistics other than entrants' relative employment are drawn from the Compustat data described in Appendix A; the model analogs of these statistics are computed from the artificial Compustat sample described in the main text.

sample are larger, invest less, and innovate more than the typical firm in our model.[18]

Fitted Parameters We choose the parameters in the left panel of Table 4 to match the targets in the right. All of the empirical targets are from our Compustat sample except for the employment of new entrants relative to incumbents, which is taken from Davis and Haltiwanger (1992) (following the strategy in Khan and Thomas 2013). Throughout, we set the exogenous growth rate g_A so that the aggregate growth rate is $g^* = 0.02$ per year and set the disutility of labor supply χ to normalize the detrended real wage to $w^* = 1$.

While all parameters are jointly chosen to match all targets, the parameters of the innovation technology are primarily disciplined by the first four targets. The regression coefficient from Section 6.1 has a strong influence on the parameters η_0 and η_1 because it determines the sensitivity of the success probability $\eta(i)$ to innovation intensity i. The mean and standard deviation of the R&D share provide further discipline on firms' incentive to innovate.

[18] Our selection procedure abstracts from changes in firms' innovation behavior associated with becoming publicly traded. See, for example, Bernstein (2015), Chemmanur, He and Nandy (2010), and Ewens and Farre-Mensa (2020) for evidence that public listing may affect firms' innovation behavior, inventor composition, and organizational choices.

Conditional on these targets, the average size of investment spikes, $\mathbb{E}[x_{jt}/k_{jt}|x_{jt}/k_{jt} > 0.2]$, disciplines the size of successful innovations Δ.

The degree of financial frictions, and the associated tangibility advantage of capital, is governed by the collateral parameter θ. Since θ governs the extent to which firms can borrow, we choose it to match average leverage in the data. The amount of borrowing early in the firms' lifecycle is heavily influenced by the initial capital stock of new entrants, k_0. We choose k_0 to match the size of new entrants relative to incumbents.

The calibrated parameter values are broadly consistent with existing estimates in the literature. The collateral parameter $\theta = 0.35$ is close to the average liquidation value of capital in bankruptcy estimated by Kermani and Ma (2023). Our innovation technology implies that the average elasticity of a successful idea with respect to innovation inputs is 0.74. In contrast, the empirical literature estimating the response of patenting to R&D spending discussed in Section 6.1 typically finds an average elasticity around 0.5 (e.g. Akcigit and Kerr 2018). One interpretation is that investment spikes capture a broader set of innovations than do patents.

Validation Appendix C studies the two sources of firm heterogeneity in the model, lifecycle dynamics and productivity differences. The model matches typical patterns of overall firm dynamics: small and young firms grow faster than other firms, while older firms are larger. Quantitatively, these relationships are close to their empirical counterparts. This validation is useful as we turn to the pecking order, which decomposes overall firm growth into components coming from capital accumulation and innovation.

Appendix C also shows that the model matches several untargeted firm-level statistics. First, the distribution of free cash flow also compares well with the data, indicating that the model's financial constraints are not unrealistically tight. For instance, more than 80% of firms have positive free cash flow in both the model and the data, and the average free-cash-flow-to-assets ratio is about 5% in the model and 8% in the data. Second, the model also matches the dispersion of leverage across firms well. Finally, the model matches the average R&D-to-sales ratio, providing further validation of the innovation technology.

Table 5
The Pecking Order: Model vs. Data

	Investment rate (1)	R&D share (2)	Patenting activity (3)
Log net worth (standardized)			
Data	−0.068	0.023	0.045
	(0.003)	(0.003)	(0.007)
Model	−0.05	0.10	0.01

Notes: results from estimating $o_{jt} = \alpha_j + \gamma \log n_{jt} + \epsilon_{jt}$, where $\log n_{jt}$ is log net worth is standardized over the entire sample. The outcomes are o_{jt} = the investment rate x_{jt}/k_{jt} in column (1), the R&D share $RD_{jt}/(RD_{jt} + x_{jt})$ where $RD_{jt} = \widetilde{A}_t(z_{jt}/Z_t)^{\frac{1}{1-\alpha-\nu}} i_{jt}$ in column (2), and an indicator for patenting in column (3). In the model, we define a patent event for firm j at time t if it received a successful innovation between period $t-1$ and t. Data estimates are the results from Section 3. Model estimates are from the artificial Compustat sample described in the main text.

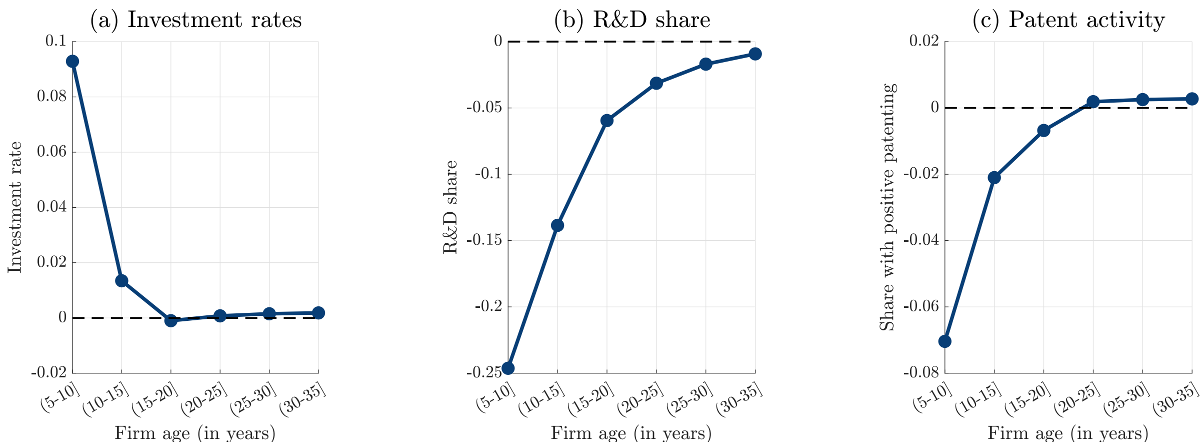
7 Financial Frictions' Role in the Pecking Order

To quantify the causal effect of financial frictions on the pecking order, we estimate the pecking order regression (1) on simulated data from the model's artificial Compustat sample. We focus on log net worth, $\log n_{jt}$, as the key right-hand side variable because it is the most directly related to the financial wedge $\lambda_t(z, n)$ in the model. Importantly, we do not expect the model to match the empirical coefficients exactly because there may be other forces, such as adjustment costs or learning by doing, which also influence the pecking order in the data.

Table 5 quantifies the model's pecking-order coefficients by net worth. Quantitatively, the model accounts for most of the negative relationship between investment and net worth, with a coefficient of −0.05 in the model compared to −0.068 in the data. The model also generates the positive relationship between the R&D share and net worth, although the slope is steeper than in the data, 0.10 compared to 0.023. This difference could reflect forces outside the model that dampen the empirical relationship, but it could also reflect measurement error in R&D expenditures, which would attenuate the empirical coefficient.

Figure 6 quantifies the model's pecking order by age using the empirical specification (2). The model replicates the qualitative life-cycle pattern in the data: young firms are investment-intensive but gradually shift to become innovation-intensive as they age. Quantitatively, firms in the 5–10 year age bin have an investment rate 0.10 higher than old firms

FIGURE 6: Model's Pecking Order by Age Bins



Notes: results from estimating $o_{jt} = \alpha_j + \sum_{s \in \mathcal{S}} \gamma_s \text{age}_{sjt} + \epsilon_{jt}$, where age_{sjt} are five-year age bins (analogous to regression specification (2) in the data). The omitted category is firms with ages $a > 40$, so all coefficients are relative to that group of firms. The outcomes are $o_{jt} =$ the investment rate x_{jt}/k_{jt} in panel (a), the R&D share $RD_{jt}/(RD_{jt} + x_{jt})$ where $RD_{jt} = \widetilde{A}_t (z_{jt}/Z_t)^{\frac{1}{1-\alpha-\nu}} i_{jt}$ in panel (b), and an indicator for patenting in panel (c). We define a patent event for firm j at time t if it received a successful innovation between period $t-1$ and t.

in the artificial Compustat sample, compared to 0.15 higher in the data. This comparison mirrors the somewhat attenuated relationship between investment and net worth described above. For the R&D share, the model predicts that young firms are 25 percentage points below old firms, compared to 6 percentage points in the data. Again, this steeper model gradient mirrors the results for net worth.

Finally, we compute the model's implications for innovation output, i.e. the arrival of new ideas. In the data, we proxied for new ideas using patenting activity but, as discussed above, not all successful innovations are patented. With this caveat in mind, we define an artificial "patenting event" in period t if the firm receives a successful innovation between periods $t-1$ and t. Table 5 shows that this measure is positively related to net worth in the model, as in the data, although the model coefficient is smaller. By contrast, Figure 6 shows that the model generates a steeper relationship between patenting and age: the patenting gap between young and old firms is 7 percentage points in the model, compared to 5 percentage points in the data.

8 Aggregate Costs of Financial Frictions

We now turn to the effects of financial frictions on aggregate productivity. We find that financial frictions robustly generate large long-run losses in aggregate productivity primarily by reducing innovation rather than by misallocating capital.

8.1 Baseline Results

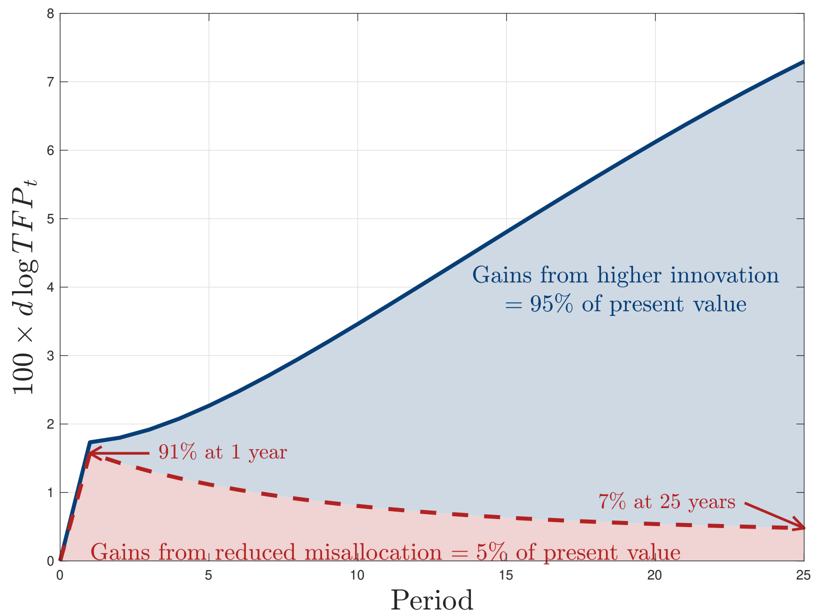
We quantify the aggregate effects of financial frictions by comparing the calibrated BGP to a counterfactual *frictionless economy*. The frictionless economy starts from the same initial BGP, but in period $t = 0$ financial frictions are removed once and for all. Thereafter, firms follow the unconstrained policies $k_t^*(z)$ and $i_t^*(z)$ and the economy transitions to a new frictionless BGP. The gap between the calibrated economy and the frictionless one captures the aggregate costs of financial frictions; equivalently, the gap between the frictionless and calibrated economy captures the gains from removing those frictions.

We study the gains of removing financial frictions for aggregate TFP. We define aggregate TFP as the Solow residual, $\text{TFP}_t = \frac{Y_t}{K_t^\alpha L_t^\nu}$, where $Y_t = \int y_{jt} dj$ is aggregate output, $K_t = \int k_{jt} dj$ is aggregate capital, and $L_t = \int \ell_{jt} dj$ is aggregate labor. Appendix B shows that this expression can be written as $\text{TFP}_t = A_t Z_t \mathcal{M}_t$, where $Z_t = \int z_{jt} dj$ and $\mathcal{M}_t = \int \frac{z_{jt}}{Z_t} \left(\frac{k_{jt}}{K_t}\right)^\alpha \left(\frac{\ell_{jt}}{L_t}\right)^\nu$. Here, Z_t is the average of firm-level productivity, which is endogenous. $\mathcal{M}_t$ captures the allocation of capital and labor across firms; it is maximized when the marginal products of capital and labor are equalized across firms. Taking log-differences between the counterfactual path and the initial BGP yields

$$\underbrace{d \log \text{TFP}_t}_{\text{total gains}} = \underbrace{d \log Z_t}_{\text{innovation}} + \underbrace{d \log \mathcal{M}_t}_{\text{misallocation}} . \tag{16}$$

Equation (16) decomposes the total gains from removing financial frictions into two components. First, the *innovation* term captures the fact that removing financial frictions increases innovation among previously constrained firms, raising the arrival rate of new ideas and thus average productivity Z_t. Second, the *misallocation* term captures the fact that removing financial frictions reduces dispersion in marginal products across firms, raising

FIGURE 7: Aggregate TFP Losses From Financial Frictions



Notes: change in log aggregate TFP between the counterfactual transition path without financial frictions and the initial BGP with financial frictions. Blue line plots total change $d \log TFP_t$ and red line plots change in misallocation $d \log \mathcal{M}_t$, so that the shaded blue area represents the change in innovation $d \log Z_t$ from (16). Present values computed using the household's discount factor β.

TFP through a higher $\mathcal{M}_t$.

Figure 7 plots the time path of the TFP gains from removing financial frictions and their decomposition in (16).[19] The gains from lower misallocation accrue immediately because resources are reallocated across firms, leading to a jump in $\mathcal{M}_t$. By contrast, the gains from higher innovation accumulate slowly over time. To understand why, take log differences of the consistency condition (10) between the counterfactual path and the initial BGP to get

$$d \log Z_{t+1} = (1 - \phi) d \log Z_t + d \log \mathcal{I}_t. \tag{17}$$

Higher innovation raises the aggregate innovation index, $d \log \mathcal{I}_t$, increasing $d \log Z_{t+1}$. These gains accumulate over time because future innovations build on the current higher level of productivity with intertemporal elasticity $1 - \phi$.

[19] In period $t = 0$, TFP does not change because the initial distribution of firms is predetermined. However, firms adopt the unconstrained policies in that period, leading to higher innovation and lower misallocation from period $t = 1$ onward.

Over the entire transition path, the gains from higher innovation account for 95% of the total TFP gains in present value terms. In our baseline calibration, $\phi = 0$, so a permanent increase $d\log \mathcal{I}_t$ leads to a permanent increase in the growth rate of Z_t. Indeed, applying equation (17) along the BGP, we get that the long-run change in the productivity growth rate satisfies $d\log(1+g_Z) = d\log \mathcal{I}$. In contrast, the gains from lower misallocation, captured by $\mathcal{M}_t$, only depend on relative shares across firms and therefore do not grow over time.

This result is the main aggregate implication of our paper: the primary cost of financial frictions to the aggregate economy is that fewer new ideas are discovered, not that existing ideas are underfunded. This finding complements the literature that studies the misallocation costs of financial frictions in models without innovation. For example, Buera, Kaboski and Shin (2011) argue that the misallocation costs of financial frictions can amount to as much as 40% of aggregate TFP in developing economies.[20] By contrast, our model is calibrated to the U.S. economy, where financial markets are much more developed and the misallocation component is much smaller.

Additional Results Appendix C contains two additional results on the effects of removing financial frictions. First, we show that the increase in the aggregate innovation index is driven by small firms that were previously constrained along the initial BGP. The resulting increase in factor prices, w_t and r_t, actually reduces the return to innovation for previously unconstrained firms, lowering their innovation intensity. Hence, equilibrium price responses reallocate innovation from large firms to small firms, highlighting the importance of a general equilibrium, heterogeneous firm model.

Second, we contrast our permanent change in financial frictions with a temporary financial shock that reduces borrowing capacity θ_t. As in Khan and Thomas (2013), the shock immediately increases misallocation, lowering aggregate TFP through a decline in $\mathcal{M}_t$. The shock also reduces innovation among constrained firms, but it does not last long enough for the decline in innovation to meaningfully reduce average productivity Z_t before the shock reverses. Hence, in contrast to the long-run effects of financial frictions, temporary financial shocks affect TFP primarily through misallocation rather than through lost innovation.

[20] Of course, the quantitative magnitudes of misallocation are debated in the literature. Midrigan and Xu (2014) argue that the TFP losses from misallocation are around 5-10% in a model calibrated to Korea.

8.2 Role of Intertemporal Knowledge Spillovers

The gains from higher innovation are especially large in our baseline because a higher aggregate innovation index permanently raises the growth rate of aggregate productivity. When $\phi > 0$, however, the economy converges to a higher level of productivity rather than to a permanently higher growth rate. The change in productivity across the initial and terminal BGPs when $\phi > 0$ is

$$d \log Z^* = \frac{1}{\phi} d \log \mathcal{I}^*.$$

Thus, for a given increase in the aggregate innovation index, the long-run increase in productivity is smaller when ϕ is larger. Moreover, solving (17) forward shows that convergence to the new steady state is faster when ϕ is larger

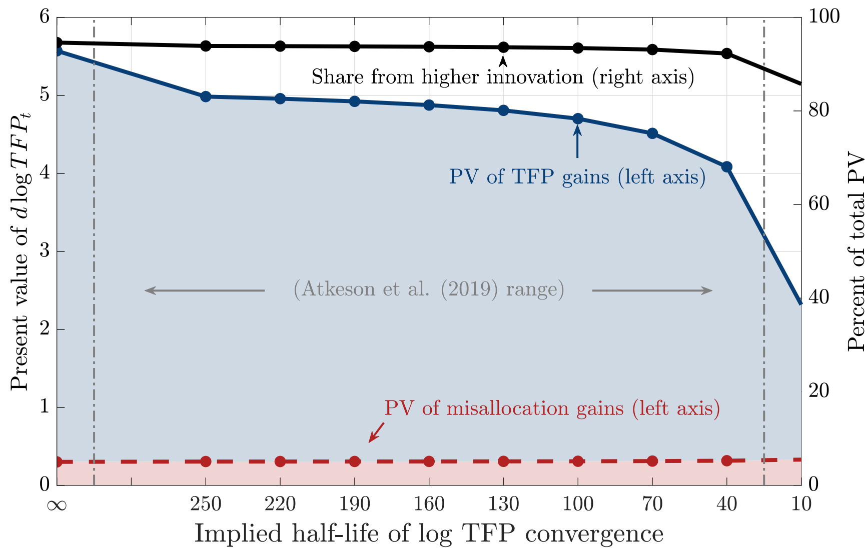
$$d \log Z_{t+1} = \left[1 - (1-\phi)^{t+1}\right] d \log Z^*. \tag{18}$$

Hence, the size of ϕ governs both the size and timing of the productivity gains from higher innovation. Unfortunately, the literature does not provide a consensus estimate of ϕ. Atkeson, Burstein and Chatzikonstantinou (2019) nest a number of quantitative models from the literature and show that the implied half-life of $\log Z_t$ to a permanent change in $\log \mathcal{I}^*$—which, from (18), is equal to $\log(1/2)/\log(1-\phi)$ in our model—ranges from 33 years to 20,794. Given the available time spans in the data and the many shocks hitting the economy at any point in time, distinguishing half-lives in this range is extremely difficult, if not impossible.[21]

Figure 8 shows our main result that the losses from financial frictions are driven primarily by lost innovation rather than misallocation for values of ϕ consistent with the range of half-lives in Atkeson and Burstein (2019). The losses are largest in our baseline with $\phi = 0$ because the half-life of the effect of higher innovation is infinite. As ϕ increases, the contribution of lost innovation to total losses declines, but remains substantial unless the implied half-life becomes quite short, for example less than ten years.

[21] Fernald and Jones (2014) and Bloom et al. (2020) attempt such estimates using different sources of data, but rely on the assumption that the economy is always on its BGP.

Figure 8: Sensitivity w.r.t. Intertemporal Knowledge Spillovers



Notes: Sensitivity analysis of the present value of TFP gains from removing financial frictions with respect to the intertemporal knowledge spillovers parameter ϕ. The x-axis is the implied half-life of a one-time increase in the aggregate innovation index $d \log \mathcal{I}^*$ on average productivity $d \log Z_t$, which is $-\log 2/\log(1-\phi)$. Vertical lines mark the range of half-lives considered in Atkeson, Burstein and Chatzikonstantinou (2019). The baseline fully endogenous growth model corresponds to $\phi = 0$ (infinite half-life). Present values computed using the household's discount factor β.

8.3 Alternative Financial Constraints and Other Sensitivity

We now show that our main results are robust to two alternative borrowing constraints. Under both alternatives, firms become less investment-intensive and more innovation-intensive as they accumulate net worth, as in the baseline model. In contrast, the model's implications for leverage depend on the form of the borrowing constraint. This distinction motivates our focus on net worth throughout the paper: net worth is the state variable that governs the financial wedge $\lambda_t(z, n)$, not leverage. Under both alternatives, removing financial frictions also generates large TFP gains, primarily through higher innovation.

Size-Dependent Constraints The first alternative constraint is motivated by two predictions of our baseline collateral constraint that are illustrated in column (1) of Table 6. Both predictions arise because the baseline constraint imposes a constant maximum leverage ratio, $b'/k' = \theta$, that is independent of firm size. Small firms have the highest desired

TABLE 6
ROBUSTNESS TO ALTERNATIVE FINANCIAL CONSTRAINTS

	(1) Baseline	(2) Size-dependent	(3) Earnings-based
Corr(leverage, $\log n$)	-0.33	0.35	-0.42
Corr(leverage, x/k)	0.06	-0.03	0.08
Pecking order coefficient	0.10	0.04	0.11
PV of TFP gains	5.57	8.32	2.73

Notes: Robustness of main results to alternative specifications of borrowing capacity $\theta_t(z,i,k')$ described in main text. First three rows report cross-sectional correlations within artificial Compustat panel in initial BGP, where leverage is defined as $b_{jt}/(k_{jt}-\min\{b_{jt},0\})$. "Pecking order coefficient" is the model-implied regression coefficient γ from running the regression $o_{jt}=\alpha_j+\gamma\log n_{jt}+\epsilon_{jt}$ for $o_{jt}=$ the R&D share $RD_{jt}/(RD_{jt}+x_{jt})$ where $RD_{jt}=\widetilde{A}_t(z_{jt}/Z_t)^{\frac{1}{1-\alpha-\nu}}i_{jt}$. "PV of TFP gains" is the present value of $d\log TFP_t$ along the transition path in which financial frictions are permanently removed in period $t=0$. Present values computed using the household's discount factor β.

investment rates and are therefore most likely to choose this maximum leverage ratio. As a result, leverage is negatively correlated with size, here measured using log net worth, and positively correlated with the investment rate. By contrast, the corporate finance literature finds the opposite pattern in the data: leverage is positively correlated with size and negatively correlated with investment (see, e.g., Rajan and Zingales 1995, Lang, Ofek and Stulz 1996, and Dinlersoz et al. 2018). One may worry that our results rely on these particular predictions of our baseline collateral constraint.

We address this concern using the size-dependent constraint $\theta_t(z,i,k')=\widetilde{\theta}\left(e^{k'}-1\right)$ proposed by Gopinath et al. (2017). We implement this alternative by holding all other parameters fixed at their baseline values and choosing $\widetilde{\theta}=0.07$ to match the same average leverage as our baseline model. Column (2) of Table 6 shows that, in our recalibration, this alternative quantitatively generates a positive correlation between leverage and size and a negative correlation between leverage and investment, as in the literature. This reversal occurs because, although small firms with the highest desired investment rates are still the most likely to be constrained, their maximum leverage ratio now increases with firm size.

Column (2) of Table 6 shows that our main results continue to hold under this size-dependent constraint. We summarize the strength of the pecking order using the regression coefficient of the R&D share on firm net worth, which provides a succinct summary of how much firms grow through innovation rather than investment. As in the baseline model, this coefficient remains positive because the financial wedge $\lambda_t(z, n)$ declines with net worth (despite the model's different implications for leverage). Moreover, removing financial frictions still generates large increases in TFP over time, primarily through higher innovation.

Earnings-Based Constraints Another concern with our baseline collateral constraint is that borrowing can only be supported by physical capital, implying an extreme tangibility difference between capital and ideas. However, recent work by Lian and Ma (2021) shows that debt contracts often include covenants tied to expected cash flows in addition to capital. To the extent that these covenants represent ex ante borrowing constraints, this evidence suggests that ideas have some collateral value through their effect on future cash flows.

We address this concern using the alternative earnings-based constraint $\theta_t(z, i, k') = \widehat{\theta}\,\mathbb{E}_t[\pi_{t+1}(z', k') \mid z, i, k']$. Because borrowing capacity is now tied to expected future profits, innovation can relax financial constraints by raising the probability of higher productivity next period. In this sense, innovation acquires collateral value: higher innovation intensity i raises current borrowing capacity and therefore enters the right-hand side of the innovation FOC (13) through the term $\mu_t(z, n)\theta_{2,t}(z, i, k')$. As before, we choose $\widehat{\theta}$ to match the same average leverage as in the baseline.[22]

Column (3) of Table 6 shows that our main results are robust to the earnings-based constraint as well. First, the model continues to generate the pecking order of firm growth. This result occurs because the technological differences still imply a steeper return schedule for capital than for innovation, even though the return to innovation now includes a collateral component. Second, removing financial frictions continues to generate large TFP gains, primarily through higher innovation.

Other Robustness Appendix C reports the sensitivity of our results to the innovation technology, the degree of financial frictions, the capital stock of new entrants, and a non-degenerate distribution of entrant productivity.

[22]Interestingly, the earnings-based constraint generates an even more negative correlation between size and leverage than the baseline. The reason is that the maximum leverage ratio is now proportional to the firm's marginal profitability of capital, which is decreasing in firm size.

9 Policy Implications

There are several reasons why the equilibrium in our model is not socially efficient. First, firms do not internalize the positive spillovers from their innovation, which may lead to under-innovation. Second, financial frictions distort the allocation of capital, even relative to a constrained planner who takes those frictions as given, due to so-called "pecuniary externalities" (see, for example, Lorenzoni 2008 and Dávila and Korinek 2018). These two sources of inefficiency interact in non-trivial ways. For example, innovation by unconstrained firms raises labor demand and therefore wages, tightening constraints for constrained firms and worsening the allocation of capital.

Fully characterizing the optimal policy is likely to be extremely complicated because the strength of these forces varies across firms and over time. In this section, we instead study the effects of simple policies that address some of these inefficiencies.[23] In particular, we compare the welfare effects of a constant investment subsidy τ^x and a constant innovation subsidy τ^i, both financed by lump-sum taxes on the household. For each policy, we assume that the economy is initially on the calibrated BGP and that the subsidy is unexpectedly and permanently introduced in period $t = 0$. Our main outcome of interest is the consumption-equivalent welfare measure ξ, which solves

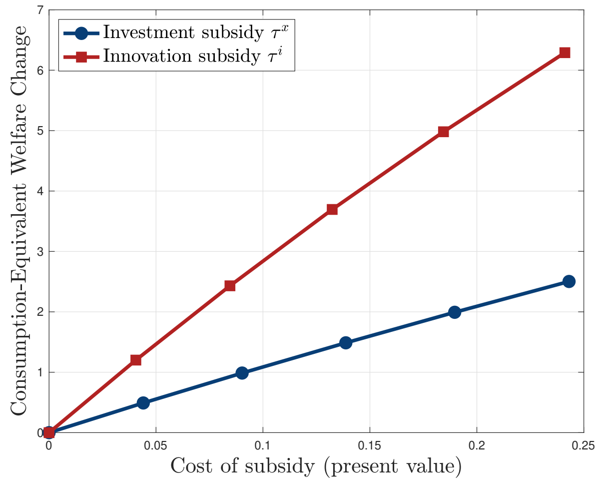
$$\sum_{t=0}^{\infty} \beta^t \left[\log((1+\xi)C_t^*) - \chi L_t^*\right] = \sum_{t=0}^{\infty} \beta^t \left[\log(C_t) - \chi L_t\right], \tag{19}$$

where C_t^* and L_t^* are the paths of consumption and labor supply on the initial BGP, and C_t and L_t are the corresponding paths under the subsidy. We compare values of the two subsidies that imply the same present value of tax revenues.

Figure 9 shows that the innovation subsidy raises household welfare by more than an investment subsidy which costs the same amount of tax revenues in present value terms. This

[23] The innovation spillovers in the baseline model are intertemporal because incumbent innovation raises Z_t, which increases the initial productivity of future entrants. For the policy analysis, we also introduce a contemporaneous spillover by setting the aggregate productivity shifter to $A_t = Z_t^{\zeta}$. This allows innovation spillovers to affect firms' current operating profits, potentially relaxing their financial constraints. We make this modification only for the illustrative policy analysis and do not use it in any of the positive exercises above. We choose ζ so that the initial BGP has annual growth $g^* = 2\%$, replacing the role of exogenous productivity growth in the baseline model.

FIGURE 9: Comparing Budget-Equivalent Policies



Notes: Welfare effect of introducing a permanent subsidy to either investment or innovation expenditures. The investment subsidy reduces firms' investment expenditures $(1-\tau^x)x_{jt}$ and the innovation subsidy reduces firms' innovation expenditures $(1-\tau^i)\widetilde{A}_t(z_{jt}/Z_t)^{\frac{1}{1-\alpha-\nu}}i_{jt}$. For each value of (τ^x, τ^i) considered, we assume the economy initially starts on the calibrated BGP, and the subsidy is permanently introduced at $t = 0$. The subsidy is financed by a lump-sum tax on households. Vertical axis plots the consumption-equivalent welfare change ξ defined in (19). Each marker corresponds to one experiment: $\tau^x \in \{0, 0.01, \ldots, 0.05\}$ with $\tau^i = 0$, or $\tau^i \in \{0, 0.015, \ldots, 0.075\}$ with $\tau^x = 0$. The present value of the cost of the subsidies is discounted at the initial BGP interest rate r^*.

result suggests that the main inefficiency in the economy stems from innovation spillovers, consistent with their importance in depressing aggregate productivity. That said, Appendix C shows that the investment subsidy also partly alleviates under-innovation because higher capital raises the incentive to innovate. Taken together, these results highlight the rich interactions between innovation spillovers and financial frictions that shape the design of optimal policy.

10 Conclusion

We have studied the efficiency costs of financial frictions in the macroeconomy. While the quantitative macro literature has primarily focused on how financial frictions distort investment decisions and misallocate capital, we have focused on how financial frictions distort the mix of investment and innovation, thereby reducing growth. We showed that these two margins are empirically linked through the pecking order of firm growth and we developed a new endogenous growth framework with heterogeneous firms and financial frictions to quantify their aggregate implications. Quantitatively, we found that the main long-run aggregate cost of financial frictions is lower innovation rather than greater misallocation. In this sense, the U.S. financial system is better at funding the implementation of existing ideas than the discovery of new ideas.

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A Data Appendix

This appendix provides additional empirical results referenced in the main text.

A.1 Data Construction

A.1.1 Annual data

Our analysis of the pecking order in Section 3 uses annual Compustat data. We describe the variables used in the empirical analysis, sample selection, and descriptive statistics in turn below.

Variables We define the variables used in our empirical analysis as follows:

1. *Investment rate*: ratio of capital expenditures (`capx`) to lagged plant, property, and equipment (`ppegt`).
2. *R&D share*: ratio of research and development expense (`xrd`) to the sum of capital expenditures and research and development expense.
3. *R&D-to-sales*: ratio of research and development expense to the average of sales (`sale`) in the previous 5 years.
4. *Patents*: Number of patents filed per year (based on the variable `filing_dated`) and market value of patents (based on the variable `xi_real`), constructed from the Kogan et al. (2017) dataset. To construct the patent-value-to-sales ratio, we use the average of sales (`sale`) in the previous 5 years.
5. *Net worth*: defined as sum of plant, property, and equipment (`ppegt`) and cash and short-term investments (`che`) minus total debt (sum of `dlc` and `dltt`).
6. *Gross leverage*: defined as total debt (sum of `dlc` and `dltt`) divided by total assets (`at`).
7. *Net leverage*: defined as total debt net of cash and short-term investments (`che`), divided by total assets (`at`).

8. *Cash flows*: measured as the sum of EBITDA and research and development expense divided by lagged plant, property, and equipment.

9. *Free cash flow*: defined as the sum of EBITDA and research and development expense, minus total income taxes (`txt`) and capital expenditures, divided by lagged total assets (`at`).

10. *Capital-to-employment*: defined as the ratio of lagged plant, property, and equipment (`ppegt`) to employment (`emp`).

In the analysis, we winsorize these variables at the top and bottom 0.5% of the distribution to ensure that the results are not driven by outliers.

Sample Selection Our empirical analysis uses the consolidated reports from Compustat North America. Aligned with standard practices in the related literature using these data (e.g., Peters and Taylor, 2017; Clementi and Palazzo, 2019; Ottonello and Winberry, 2020), our analysis excludes:

1. Firms in finance, insurance, and real estate sectors ($\texttt{sic} \in [6000, 6799]$), utilities ($\texttt{sic} \in [4900, 4999]$), nonoperating establishments ($\texttt{sic} = 9995$), and industrial conglomerates ($\texttt{sic} = 9997$).

2. Firms not incorporated in the United States.

3. Firm-year observations that satisfy one of the following conditions, aimed at excluding extreme observations:

   i. Negative assets, sales, capital expenditure, or R&D.

   ii. Low capital values (gross plant, property, and equipment below $5M in 1990 dollars).

   iii. Acquisitions larger than 20% of assets.

   iv. Investment rates higher than 1.

   v. R&D-to-sales ratios higher than 0.3.

   vi. Gross leverage higher than 10 or negative.

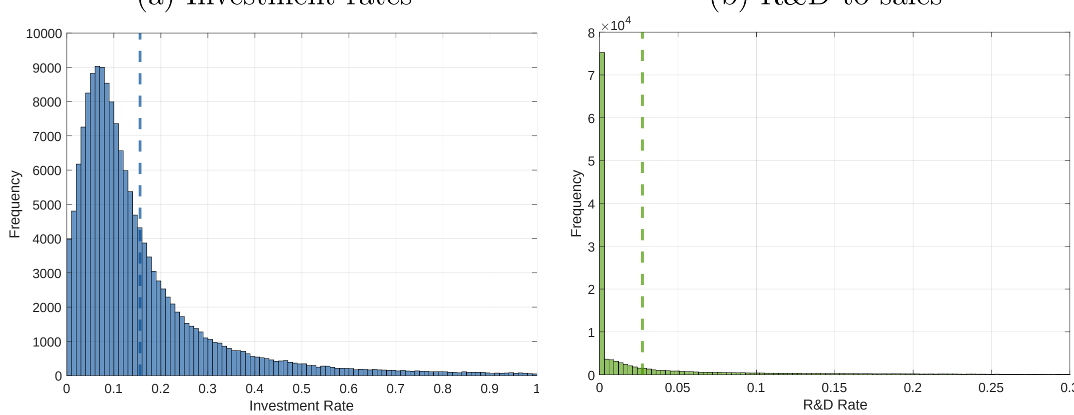
Appendix Table A.3 shows that our results are robust to excluding any of these sample restrictions. In estimating the regressions in Tables 2 and A.7, we follow Ottonello and Winberry (2020) and further restrict the sample to investment spells lasting at least 10 years to more precisely estimate firm fixed effects.

The age-conditional analyses (Figure 2 and specifications that include age) restrict the sample to firms with a Datastream incorporation year, which we match to Compustat by CUSIP. For firms whose recorded incorporation year falls after their first appearance in Compustat, we set the incorporation year equal to the first Compustat year. In Figure 5, we exclude such firms from the sample, as their incorporation data appears more likely to correspond to events such as divisional spinoffs, reincorporations in Delaware, or reverse LBOs. In addition, in the sample used for Figure 5, we do not apply the $5 million real-capital floor in item [3.] of the sample selection procedure in order to preserve firms that enter Compustat at a small size. In estimating the regressions in Tables 2 and A.7, we follow Ottonello and Winberry (2020) and restrict the sample to investment spells lasting at least 10 years in order to more precisely estimate firm fixed effects.

Descriptive Statistics Table A.1 contains descriptive statistics of our final analysis sample. Figure A.1 plots the distribution of investment rates and R&D-to-sales ratios in our sample.

FIGURE A.1: Distribution of Investment Rates and R&D

(a) Investment rates (b) R&D-to-sales



Notes: This figure shows the histogram of investment rates and the R&D-to-sales ratio. Vertical dashed lines represent each variable's mean. For variable definitions and sample selection, see Appendix A.1.

TABLE A.1
DESCRIPTIVE STATISTICS

	Mean	Median	St dev	95th	Obs.
Investment rate	.156	.107	.154	.481	158,112
Investment spike	.233		.423		158,112
Investment rate | spike	.374	.312	.175	.781	36,847
Time since last spike	4.37	2	6.13	17	112,488
R&D share	.193		.292	.845	166,452
R&D-to-sales ratio	.027	0	.056	.165	125,973
Positive R&D expenditure	.382		.486		186,437
R&D-to-sales ratio | positive R&D expenditure	.064	.033	.07	.224	53,990
Leverage	.285	.243	.256	.741	168,823

Notes: This table shows descriptive statistics for variables used in the empirical analysis of Section 6.1. Investment rate, R&D-to-sales ratio, and leverage are defined in Appendix A.1. *Investment spike* denotes a dummy variable that takes the value of one in periods in which a firm's investment rate is above 20%. *Time since last spike* denotes the number of years since the firm experienced the previous investment spike. *Positive R&D expenditure* denotes a dummy variable that takes the value of one in a period in which a firm's research and development expense (`xrd`) is positive. *Investment rate* | *spike* and *R&D-to-sales ratio* | *positive R&D expenditure* report, respectively, moments for investment rates conditional on periods of investment spikes and of R&D-to-sales ratios conditional on positive R&D expenditure. For sample selection, see Appendix A.1.

A.1.2 Quarterly Data

Our analysis of financial shocks in Section 3.3 uses quarterly Compustat variables together with a firm-level measure of financial shocks. We describe each in turn below.

Compustat variables We apply similar sample restrictions to the quarterly Compustat as to the annual sample described above.[24] In addition, we apply the sample restrictions from Ottonello and Winberry (2020) designed for quarterly Compustat data. The firm-level outcomes $y_{j,t+h}$ in equation (3) are:

1. *Debt*: $(\text{Debt}_{j,t+h} - \text{Debt}_{j,t-1})/A_{j,t-1}$, where $\text{Debt}_{j,t}$ denotes firm j's total debt in period t (sum of short-term debt `dlcq` and long-term debt `dlttq`), and $A_{j,t}$ denotes firm j's total assets in period t (`atq`).

[24] We adapt the restrictions in item [3.] of the sample selection section to the quarterly frequency as follows. For (ii), we apply the $5 million floor to the physical capital measure $K_{j,t}$ described above, given the high incidence of missing values for the variable `ppegtq`. For (iii), we apply the 20% threshold to year-to-date acquisitions (`aqcy`). For (v), we apply the restriction to trailing four-quarter R&D divided by the average sales of the previous three years.

2. *External finance*: $(\text{Debt}_{j,t+h} - \text{Debt}_{j,t-1} + \text{Equity}_{j,t+h} - \text{Equity}_{j,t-1})/A_{j,t-1}$, where $\text{Equity}_{j,t}$ denotes firm j's book value of equity in period t (atq−ltq).

3. *R&D share*: $\sum_{s=t}^{t+h} \texttt{xrdq}_{j,s} \,/\, \sum_{s=t}^{t+h}(\texttt{xrdq}_{j,s} + \texttt{capxq}_{j,s})$, where $\texttt{xrdq}_{j,s}$ denotes firm j's research and development expense in period s and $\texttt{capxq}_{j,s}$ denotes firm j's capital expenditures in period s (constructed by differencing the year-to-date capxy). In our baseline, we code this variable as missing in the periods before the firm reports its first positive R&D expenditure, to reduce measurement error in quarterly R&D reporting (following our analysis using annual data in Appendix A.2). We estimate a similar elasticity when we instead treat these observations as zeros.

4. *Physical capital*: $\log K_{j,t+h} - \log K_{j,t-1}$, where $K_{j,t}$ denotes firm j's physical capital in period t. To construct $K_{j,t}$, we follow Clementi and Palazzo (2019) and Ottonello and Winberry (2020), initializing it with the first non-missing observation of gross property, plant, and equipment (ppegtq) and updating it each quarter by adding the change in net property, plant, and equipment (ppentq), linearly interpolating isolated missing ppentq observations from adjacent quarters.

5. *Intangible assets*: $\log \text{INTAN}_{j,t+h} - \log \text{INTAN}_{j,t-1}$, where $\text{INTAN}_{j,t}$ denotes firm j's balance-sheet intangibles (intanq) in period t.

When estimating equation (3), we winsorize these dependent variables at the 0.5th and 99.5th percentiles. The leverage indicator $x_{j,t-1}$ equals one if firm j's lagged leverage, defined as the ratio of total debt to total assets ((dlcq+dlttq)/atq), is above its firm-specific mean. In the vector of controls $Z_{j,t-1}$, following Ottonello and Winberry (2020) we include sales growth, size, current assets as a share of total assets, together with the log number of lenders in the firm's most recent syndicated loan, $x_{j,t-1}$, and $\rho_t \times x_{j,t-1}$. We also include firm by fiscal-quarter fixed effects, to account for the fact that a fraction of firms report R&D expenditures only at fiscal year-end. The sector-by-time fixed effects, α_{sth}, interact quarter dummies with broad industry groups, defined as the one-digit SIC divisions (as in Ottonello and Winberry, 2020).

Financial shocks We construct the financial shock v_{jt} used in Section 3.3 in two steps.

1. *High-frequency firm–bank shock.* The bank-level shock, Δp^F_{it}, for intermediary $i \in \mathcal{I}$ is the broad, unweighted measure from Ottonello and Song (2025), where $\mathcal{I}$ denotes the set of intermediaries in their sample. Building on Chodorow-Reich (2014), the exposure indicator θ_{jit} equals one if intermediary i is the lead arranger on firm j's most recent syndicated loan prior to intermediary i's earnings announcement in quarter t, and zero otherwise.[25] In Dealscan this corresponds to the `leadarrangercredit` variable taking the value "Yes." We obtain firm–bank lending relationships from Dealscan, restricting the sample to syndicated loans originated between 1993 and 2020 for corporate purposes or working capital by US borrowers with non-missing state and industry identifiers. We match Dealscan facilities to Compustat using the linking database of Chava and Roberts (2008). For each shock event, we select the borrower's most recently originated facility that is still active at the time of the shock. Using these data, we construct the high-frequency firm–bank shock as $\epsilon^F_{jit} = \theta_{jit}\, \Delta p^F_{it}$.

2. *Quarterly firm-level shock.* We aggregate the high-frequency firm–bank shocks across intermediaries and quarters using a day-weighted moving average, as in Ottonello and Winberry (2020): $\varepsilon^F_{jt} = \sum_{i \in \mathcal{I}_t} \omega^a_{it}\, \epsilon^F_{jit} + \sum_{i \in \mathcal{I}_{t-1}} \omega^b_{i,t-1}\, \epsilon^F_{ji,t-1}$, where $\mathcal{I}_t$ is the set of intermediaries with earnings announcements in quarter t, $\omega^a_{it} \equiv (\tau^n_{it} - \tau^d_{it})/\tau^n_{it}$, and $\omega^b_{it} \equiv \tau^d_{it}/\tau^n_{it}$, with τ^d_{it} the day of intermediary i's earnings announcement in the quarter and τ^n_{it} the number of days in the quarter. We then standardize ε^F_{jt} pooling all firms and quarters and set $v_{jt} \equiv \varepsilon^F_{jt} \times \rho_t$, where ρ_t is an indicator equal to one during the Great Financial Crisis (2008Q1–2009Q2) and zero otherwise.

Additional results Figure A.2 reports the estimated effects of financial shocks on additional outcomes mentioned in the main text: debt, external finance, and capital.

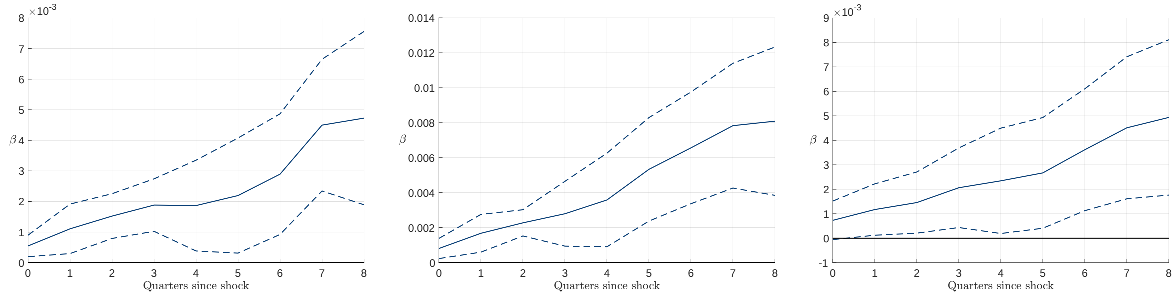
A.2 Robustness of Pecking Order

This section contains the additional robustness analysis described in the main text. We recapitulate that description below.

[25] If the firm's most recent loan deal involves no intermediary in $\mathcal{I}$, or if the firm has no syndicated loan outstanding at the time of the shock, the firm receives a missing value in that period.

FIGURE A.2: The Effects of Financial Shocks – Additional Firm-Level Outcomes

(a) Debt (b) External Finance (c) Capital



Notes: This figure reports the dynamic effects of financial shocks on high-leverage firms' outcomes, obtained from estimating

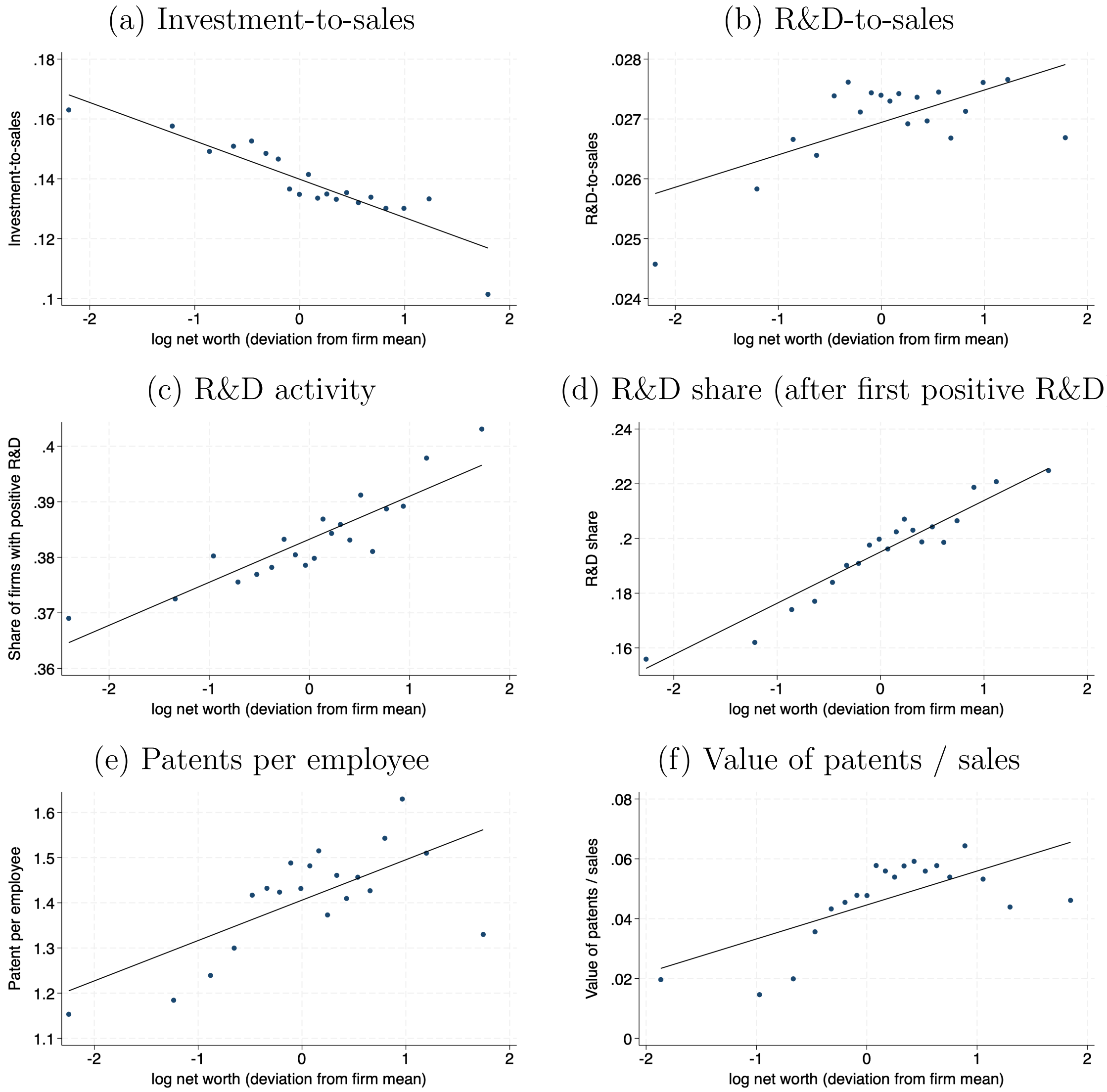
$$y_{j,t+h} = \alpha_{jh} + \alpha_{sth} + \beta_h v_{jt} + \gamma_h v_{jt} x_{j,t-1} + \Gamma'_h Z_{j,t-1} + \varepsilon_{jth},$$

where y_{jt+h} is a firm-level outcome; v_{jt} is the firm-level financial shock (standardized); x_{jt-1} is a dummy variable if firm j's leverage is above its firm-specific mean in period $t-1$; α_{jh} and α_{sth} denote firm and sector-by-time fixed effects; and $Z_{j,t-1}$ is a vector of controls that includes sales growth, size, current assets as a share of total assets, firm-by-fiscal-quarter dummies, the log number of lenders in the firm's most recent syndicated loan, x_{jt-1}, and $\rho_t x_{jt-1}$. Each panel reports $\Gamma_h = \hat{\beta}_h + \hat{\gamma}_h$ for a different outcome y_{jt+h}: debt, external finance, and capital. Dashed lines report 90% confidence bands based on standard errors two-way clustered by firm and quarter. For variable definitions and sample selection, see Appendix A.

Figure A.3 shows that our bin-scatter plots look similar for other measures of investment and innovation. Panel (a) shows that the investment-to-sales ratio is declining in net worth, similar to the investment-to-capital ratio presented in the main text. The remaining panels show that other measures of innovation are increasing in net worth: panel (b) is the ratio of R&D expenditures to sales, which is often studied in the literature; panel (c) is the share of firms with positive R&D, a measure of the extensive margin; panel (d) is the R&D share for firms once they have first reported positive R&D, and therefore have presumably set up the accounting infrastructure to record formal R&D with less measurement error; panel (e) is the patents-to-employees ratio, another measure often studied in the literature; and panel (f) is the total market value of new patents granted in a given year (scaled by firms' sales), which provides a measure of overall patent quality.

Table A.2 shows that the pecking order is generally robust to using different sources of variation in the data. Panel (a) reports the regression coefficients (1) without the firm fixed effects α_j. Panel (b) then includes firm fixed effects, which is our baseline specification from the main text. Panel (c) replaces the firm fixed effects with 4-digit sector fixed effects α_s. Panel (d) includes sector-by-year fixed effects α_{st} to focus on within-sector-year variation.

Figure A.3: The Pecking Order of Firm Growth for Other Measures of Investment and Innovation



Notes: Binned scatter plots of the investment-to-sales ratio, the R&D-to-sales ratio, the share of firms with positive R&D, the R&D share (conditional on already having an observation with positive R&D), patents per employee, and market value of patents relative to sales by the log of firm net worth. All variables are demeaned at the firm level. In order to make the units of the outcome variables more interpretable, we add back in the unconditional mean of the outcome variables across all firms. For variable definitions and sample selection, see Appendix A.

Finally, panel (e) includes firm and year fixed effects to absorb aggregate trends in the outcome variables.

Table A.3 shows that the pecking order is also robust when using different samples of firms. Panel (a) reports results using all firms and periods without the sample restrictions

TABLE A.2
SOURCES OF VARIATION IN THE PECKING ORDER

	(1) Investment rate	(2) R&D share	(3) Patent activity
(a) No fixed effects			
$\hat{\gamma}$	-0.010	-0.012	0.101
	(0.001)	(0.001)	(0.002)
N	45671	47020	48943
Adjusted R^2	0.009	0.003	0.047
(b) Firm fixed effects (baseline)			
$\hat{\gamma}$	-0.068	0.023	0.045
	(0.003)	(0.003)	(0.007)
N	45667	47016	48939
Adjusted R^2	0.260	0.853	0.638
(c) Sector fixed effects			
$\hat{\gamma}$	-0.014	0.018	0.155
	(0.001)	(0.003)	(0.007)
N	45671	47020	48943
Adjusted R^2	0.085	0.575	0.357
(d) Sector $\times$ year fixed effects			
$\hat{\gamma}$	-0.001	0.013	0.196
	(0.002)	(0.004)	(0.008)
N	42539	43847	45871
Adjusted R^2	0.200	0.559	0.354

Notes: Panel (a) shows the results from estimating the regression $o_{jt} = \alpha + \gamma \log n_{jt} + \epsilon_{jt}$, where o_{jt} is the outcome of interest (investment rate, R&D share, or an indicator for positive patenting); and n_{jt} is net worth (standardized over the whole sample). Panel (b) shows our baseline results, from estimating the regression $o_{jt} = \alpha_j + \gamma \log n_{jt} + \epsilon_{jt}$, where α_j is a firm fixed effect. Panel (c) reports the results from estimating $o_{jt} = \alpha_s + \gamma \log n_{jt} + \epsilon_{jt}$, where α_s is a sector fixed effect. Panel (d) reports the results from estimating $o_{jt} = \alpha_{st} + \gamma \log n_{jt} + \epsilon_{jt}$, where α_{st} is a sector-by-time fixed effect. For variable definitions and sample selection, see Appendix A.

described in Appendix A.1 (#3 of sample selection, items (i)–(vi)). Panel (b) applies these sample restrictions, but does not select firms that have at least twenty years of observations as in our baseline sample. Panel (c) uses our baseline sample from the main text. Finally, panel (d) conditions on Akcigit and Kerr (2018)'s definition of "continuously innovative firms" in our baseline sample, i.e., firms which have at least twenty years of observations and have conducted positive R&D or patenting activity over the previous five years.

Table A.3

The Pecking Order of Firm Growth for Alternative Samples

	(1) Investment rate	(2) R&D share	(3) Patent activity
(a) All firms and periods, w/o sample restrictions			
$\hat{\gamma}$	-0.081	0.009	0.052
	(0.005)	(0.002)	(0.002)
N	280661	301419	317618
Adjusted R^2	0.211	0.872	0.565
(b) All firms and periods, with sample restrictions			
$\hat{\gamma}$	-0.061	0.020	0.058
	(0.002)	(0.002)	(0.004)
N	134940	140726	142521
Adjusted R^2	0.322	0.889	0.612
(c) Baseline sample (20-year spell)			
$\hat{\gamma}$	-0.068	0.023	0.045
	(0.003)	(0.003)	(0.007)
N	45667	47016	48939
Adjusted R^2	0.260	0.853	0.638
(d) Sample of continuously innovative firm			
$\hat{\gamma}$	-0.063	0.040	0.043
	(0.003)	(0.005)	(0.011)
N	26700	27384	28556
Adjusted R^2	0.264	0.801	0.476

Notes: This table shows the results from estimating the regression $o_{jt} = \alpha_j + \gamma \log n_{jt} + \epsilon_{jt}$, where o_{jt} is the outcome of interest (investment rate, R&D share, or an indicator for positive patenting); n_{jt} is net worth (standardized over the whole sample); and α_j is a firm fixed effect.
Panel (a) reports results using all firms and periods without the sample restrictions described in Appendix A.1 (#3 of sample selection, items (i)–(vi)); panel (b) applies these sample restrictions, but does not select firms that have at least twenty years of observations as in our baseline sample; panel (c) shows our baseline sample, including firms with at least 20 years of observations; and panel (d) the sample of firms with at least 20 years of observations and that are "continuously innovative" (i.e., firms that have conducted positive R&D or patenting activity over the last five years). For variable definitions and sample selection, see Appendix A.

Table A.4 shows that the pecking order by net worth is robust to the inclusion of additional controls. Panel (a) reports the baseline specification with firm fixed effects and no controls. Panel (b) adds firm size dummies based on employment quintiles, and panel (c) further adds age dummies. The pecking order pattern remains statistically significant across

Table A.4
The Pecking Order of Firm Growth in Multivariate Regressions

	(1) Investment rate	(2) R&D share	(3) Patent activity
(a) Baseline (no controls)			
$\hat{\gamma}$	-0.068	0.023	0.045
	(0.003)	(0.003)	(0.007)
N	45667	47016	48939
Adjusted R^2	0.260	0.853	0.638
(b) Controlling for size dummies			
$\hat{\gamma}$	-0.072	0.028	0.023
	(0.003)	(0.003)	(0.008)
N	44571	45761	47578
Adjusted R^2	0.261	0.855	0.644
(c) Controlling for size and age dummies			
$\hat{\gamma}$	-0.040	0.011	0.041
	(0.004)	(0.004)	(0.013)
N	24872	25333	25910
Adjusted R^2	0.306	0.862	0.643
(d) Controlling for cash intensity			
$\hat{\gamma}$	-0.069	0.021	0.048
	(0.003)	(0.003)	(0.007)
N	45667	47016	48939
Adjusted R^2	0.262	0.854	0.639

Notes: Each panel reports $\hat{\gamma}$ from estimating the regression $o_{jt} = \alpha_j + \gamma \log n_{jt} + \mathbf{x}'_{jt}\boldsymbol{\beta} + \epsilon_{jt}$, where o_{jt} is the outcome of interest; n_{jt} is net worth (standardized over the whole sample); α_j is a firm fixed effect; and $\mathbf{x}_{jt}$ is a vector of additional controls. Panel (a) reports the baseline specification (no additional controls). Panel (b) adds employment quintile dummies (within year). Panel (c) adds both size and age dummies (5-year bins of age since incorporation, with >35 omitted). Panel (d) adds cash intensity, defined as the ratio of cash and short-term investments to the sum of cash and short-term investments and plant, property, and equipment. Standard errors, reported in parentheses, are clustered at the firm level. The sample is restricted to firms with at least twenty years of observations. For variable definitions and sample selection, see Appendix A.

all three outcomes, with somewhat attenuated magnitudes when controlling for both size and age, consistent with these variables being correlated with net worth. Panel (d) adds cash intensity, showing that the pecking order by net worth is not driven by a link between firms' innovation decisions and their demand for liquid assets.

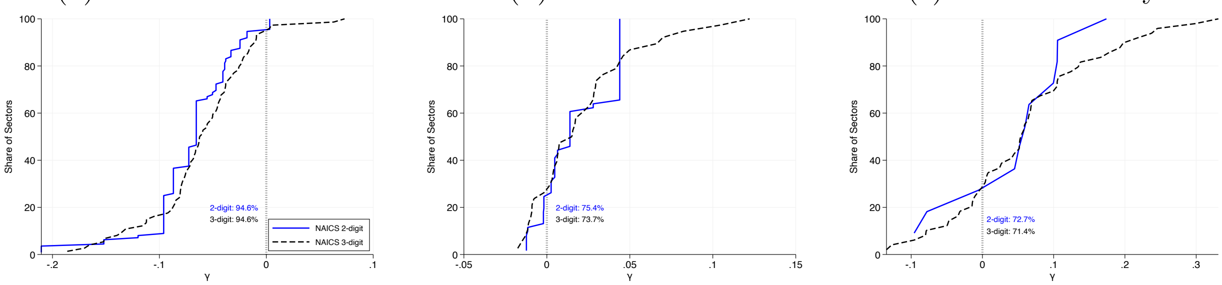
A.3 Sectoral Analysis

This section analyzes the pecking order of firm growth by sector. We conduct two exercises.

First, we estimate the pecking order regression (1) separately using data from each 2-digit and 3-digit NAICS sector.[26] Figure A.4 shows the empirical cumulative distribution function of the estimated coefficients $\{\hat{\gamma}_i\}$ across sectors. Panel (a) shows that almost all sectors (95%) are characterized by a negative relationship between investment rates and net worth. Panel (b) shows that the majority of sectors (75%) exhibit a positive relationship between the R&D share and net worth, while panel (c) shows that the majority of sectors (74% and 83%) exhibit a positive relationship between patent activity and net worth. Therefore, the pecking order of firm growth documented in Section 3 is pervasive across sectors.

Figure A.4: The Pecking Order of Firm Growth: Distribution of Sectoral Estimates

(a) Investment rate (b) R&D share (c) Patent activity



Notes: Cumulative distribution function of sector-level coefficients $\hat{\gamma}_i$ from estimating $o_{jt} = \alpha_j + \gamma_i \log n_{jt} + \epsilon_{jt}$ separately within each industry i. Two industry classifications are used: NAICS 2-digit (solid blue) and NAICS 3-digit (dashed black). The dotted vertical line indicates $\gamma = 0$. Industries with fewer than 3 firms, fewer than 10 observations, or more than 90% zero values are excluded. The reported numbers indicate the share of sectors with a negative coefficient in panel (a) and a positive coefficient in panels (b)–(c).

Our second exercise analyzes how the pecking order varies with sectoral characteristics. Motivated by the model discussion in Section 5.2, we focus on the pledgeability of capital, captured in our model by the collateral parameter θ. Following a large empirical literature (Rajan and Zingales, 1995; Claessens and Laeven, 2003; Almeida and Campello, 2007), we measure pledgeability across sectors using the share of tangible fixed assets in total assets (PPENT/AT). We construct the empirical proxy $\hat{\theta}_i$ for sectoral pledgeability as the NAICS

[26] Sectors with fewer than three firms, fewer than ten observations, or more than 90% zeros in the outcome are excluded to avoid degenerate regressions with near-constant outcomes.

4-digit sector median of this firm-level ratio, standardized over the full sample.[27]

Using this measure, we estimate the interaction regression

$$o_{jt} \;=\; \alpha_j + \gamma_0 \log s_{jt} + \gamma_\theta \left(\log s_{jt} \times \hat{\theta}_{i(j)}\right) + \varepsilon_{jt}, \tag{20}$$

where o_{jt} is the outcome of interest (investment rate, R&D share, or patenting activity); α_j is a firm fixed effect; $\log s_{jt}$ is the size or age measure along which we trace the pecking order, namely log net worth, log capital, or log age; and $\hat{\theta}_{i(j)}$ is the empirical proxy for sectoral pledgeability defined above, with $i(j)$ denoting the NAICS 4-digit sector of firm j. The coefficient γ_0 captures the average pecking-order slope, and γ_θ captures how the slope varies across sectors with different tangibility.

Table A.5 reports the results from estimating equation (20) for different specifications. Columns (1)–(3) show that, overall, higher pledgeability is associated with a less steep pecking order, consistent with the model prediction that greater borrowing capacity allows firms to start innovating earlier in their life cycle. For instance, the slope of the R&D share on net worth is about 0.017 smaller per additional standard deviation of sectoral tangibility (column (2)), roughly 70% of the average slope. While the statistical significance of the interaction coefficients varies across specifications, the overall pattern supports the model's prediction about how sectoral heterogeneity shapes the pecking order.

A.4 Illustrative Examples of the Pecking Order of Firm Growth in Earnings Calls

This section provides illustrative examples of the pecking order of firm growth using a textual analysis of earnings calls from U.S. publicly traded firms. To do so, we use `NL Analytics`, a platform that compiles more than 400,000 earnings call transcripts and provides text-analytics tools building on work such as Bloom et al. (2021) and Hassan et al. (2024). Using this platform, we searched for sentences containing terms related to investment, R&D, innovation, capital expenditures, financial constraints, and the allocation between tangible

[27] For firms whose Compustat NAICS is reported at fewer than four digits, we group at the finest available level (3- or 2-digit).

Table A.5
The Pecking Order of Firm Growth: Heterogeneity by Sectoral Asset Pledgeability

	(1) Investment rate	(2) R&D share	(3) Patent activity
(a) Log Net Worth			
$\hat{\gamma}_0$	-0.068	0.024	0.047
	(0.003)	(0.003)	(0.007)
$\hat{\gamma}_\theta$	0.000	-0.016	-0.017
	(0.003)	(0.002)	(0.006)
N	45667	47016	48939
Adjusted R^2	0.260	0.854	0.639
(b) Log Capital			
$\hat{\gamma}_0$	-0.088	0.027	0.065
	(0.003)	(0.004)	(0.009)
$\hat{\gamma}_\theta$	0.012	-0.017	-0.026
	(0.004)	(0.003)	(0.007)
N	49714	51293	53498
Adjusted R^2	0.269	0.849	0.632
(c) Log Age			
$\hat{\gamma}_0$	-0.082	0.024	0.033
	(0.004)	(0.004)	(0.008)
$\hat{\gamma}_\theta$	0.015	-0.014	-0.006
	(0.004)	(0.003)	(0.005)
N	16229	16947	18283
Adjusted R^2	0.301	0.871	0.598

Notes: Results from estimating $o_{jt} = \alpha_j + \gamma_0 \log s_{jt} + \gamma_\theta(\log s_{jt} \times \hat{\theta}_{i(j)}) + \epsilon_{jt}$, where o_{jt} is the outcome; s_{jt} is the measure of size (standardized); $\hat{\theta}_{i(j)}$ is the empirical proxy for sectoral pledgeability, defined as the sector-level median of the tangibility ratio PPENT/AT, with $i(j)$ denoting the NAICS 4-digit sector of firm j; and α_j is a firm fixed effect. Sector medians are computed within each NAICS 4-digit industry and standardized. Standard errors clustered at the firm level.

and intangible assets.

We document specific cases in which firms explicitly discuss the tradeoff between investment and innovation, as well as the role played by financial frictions in shaping these decisions.

Table A.6

Selected Transcript Excerpts Illustrating the Pecking Order of Firm Growth

Company	**Industry**	**Date**	**Transcript excerpts**
Panel A: Investment and innovation			
ConAgra Foods Inc	Food & Beverages	2011-03	As we've said before, the mix of our capital expenditures continues to shift away from infrastructure and to more innovation and growth investments.
First Solar Inc	Renewable Energy	2011-11	We are reallocating overhead and reducing CapEx to fund increased investments in market development, sales, R&D, and to improve operating margins.
Invensys Ltd	Industrial Goods	2010-11	As we promised, we have shifted and reduced our spending on restructuring and on tangible capital expenditures and reappointed the investment in operating R&D and development of new product portfolios.
Tilray Inc	Pharma & Medical Research	2019-11	Our global growth strategy remains unchanged: First, selectively increase our production and manufacturing capacity... second, maintain a rigorous focus on quality as we scale; third, partner with established distributors... and finally, sixth, pioneer the future of our industry by investing in innovation, R&D and clinical research.
Umicore SA	Chemicals	2006-02	Whilst our Group is becoming probably less capital expenditure intensive we've certainly become more R&D intensive and thus, in a rather significant way, you can see that our R&D expenditure has, in view of the shifting nature of the Group, tripled or more than quadrupled since 2002 reaching 112 million.
Panel B: Financial frictions, investment, and innovation			
Acciona SA	Industrial & Commercial Services	2014-02	In the short-term, the overriding priority is to reduce our credit risk by strengthening our balance sheet and protecting our liquidity even if this comes at the expense of dividends, R&D, capacity, SG&A or, of course, CapEx.
Baxter International Inc	Healthcare Services & Equipment	2009-01	I think one of these I'm most pleased about as I reflect back on the last four or five years, is that as a result of our improving financial performance, we have been able to fund a fairly dramatic ramp up in R&D, and the nature of our pipeline has changed.
Daimler AG (Mercedes-Benz)	Automobiles & Auto Parts	2015-10	We rely on our financial strength and strong balance sheet to safeguard our ability to invest in products, technology, innovation, and production activities.

Table A.6 (continued)

Company	Industry	Date	Transcript excerpts
Panel B: Financial frictions, investment, and innovation (continued)			
Ipsen SA	Pharma & Medical Research	2015-03	And this very strong cash flow has been used to finance first our industrial CapEx in order to support the growth of our business and to support our new R&D model.
IXYS Corp	Technology Equipment	2012-08	We have the financial fire power to ramp up our R&D investment throughout the power spectrum, while our sales team work to capture business from other competitors.
Juniper Networks Inc	Technology Equipment	2008-10	We have been conservative in our investment strategies with regards to our cash, and with no debt on our balance sheet, we are in a very comfortable position to continue to grow our business and execute on our R&D priorities.
NeurogesX Inc	Pharma & Medical Research	2009-03	As a result, we have deferred all R&D activities for Qutenza, our follow-on liquid formulation NGX-1998, and our preclinical prodrug programs until we secure additional funds through a partnership or non-equity based financing.
NXP Semiconductors NV	Technology Equipment	2015-07	There's a large number of subscale semiconductor companies that cannot afford the long-term R&D investment, the intellectual property, the competitive manufacturing cost base… not having sufficient scale to be able to drive volumes with the foundries.
Paradigm Genetics Inc	Pharma & Medical Research	2003-11	We have made excellent financial progress so far, allowing us to prudently ramp up and commit to our R&D programs.
Xyratex Ltd	Technology Equipment	2011-01	Independent specialized equipment companies lack the business scale and global support infrastructure necessary to fund the accelerated R&D investments. Xyratex's business scale and global infrastructure will provide the operational efficiency leverage that is necessary to enable the business model to maintain high levels of R&D investment in capital equipment innovation.

Notes: This table presents 15 excerpts from earnings-call transcripts of U.S. and international publicly traded firms. Excerpts were identified using `NL Analytics`, a platform that compiles more than 400,000 earnings call transcripts and provides text-analytics tools building on Hassan et al. (2024). We searched for sentences containing terms related to investment, R&D, innovation, capital expenditures, financial constraints, and the allocation between tangible and intangible assets.

Table A.7
Investment Spikes and Innovation: Robustness

	(1)	(2)	(3)	(4)	(5)
$\frac{R\&D_{t-1}}{y_{t-1}}$	1.168	0.723	1.172	1.113	1.145
	(0.135)	(0.141)	(0.135)	(0.147)	(0.141)
Measure of spikes	Absolute	Sectoral	Absolute	Absolute	Absolute
R&D lags	4	4	3	5	4
Additional controls	No	No	No	No	Size, sales growth, current assets
Observations	48,293	33,080	48,293	44,659	46,964
Adj. R^2	0.312	0.223	0.312	0.304	0.323

Notes: Results from estimating $\mathbb{1}\{\frac{x_{jt}}{k_{jt}} \geq \chi_s\} = \alpha_j + \alpha_{st} + \sum_{h=1}^{H} \beta_h \left(\frac{\text{RD}_{jt-h}}{\tilde{y}_{jt-h}}\right) + \Gamma' X_{jt} + \epsilon_{jt}$, where $\frac{x_{jt}}{k_{jt}}$ denotes the investment rate of firm j in period t; χ_s is a threshold defining investment spikes; $\frac{\widehat{i}_{jt}}{\tilde{y}_{jt}}$ the R&D-to-sales ratio; α_j and α_{st} are firm and time by sector fixed effects; $X_{j,t}$ is a vector of firm-level controls; and ϵ_{jt} is a residual. Column (1) reports estimates for the baseline specification of Table 2, with $\chi_s = 0.2$, $H = 1$, and the vector X_{jt} including cash flows ($\frac{\text{cf}_{jt}}{k_{jt}}$) and the lumpy-investment controls (years since the last investment spike, years since spike$_{t-1}$, and the (lagged) standardized capital-employment ratio, $\frac{k_{jt-1}}{\ell_{jt-1}}$). Column (2) uses a "sectoral" threshold for investment spikes, where χ_{ts} is the mean plus one standard deviation of the distribution of investment rates of sector s (at 2-digit NAICS level). Columns (3) and (4) report results for alternative lags of the R&D-to-sales ratio: $H = 3$ and $H = 5$. Column (5) includes additional control variables: size (measured with the log of real plant, property, and equipment), sales growth, and the share of current assets. For variable definitions and descriptive statistics, see Appendix A.

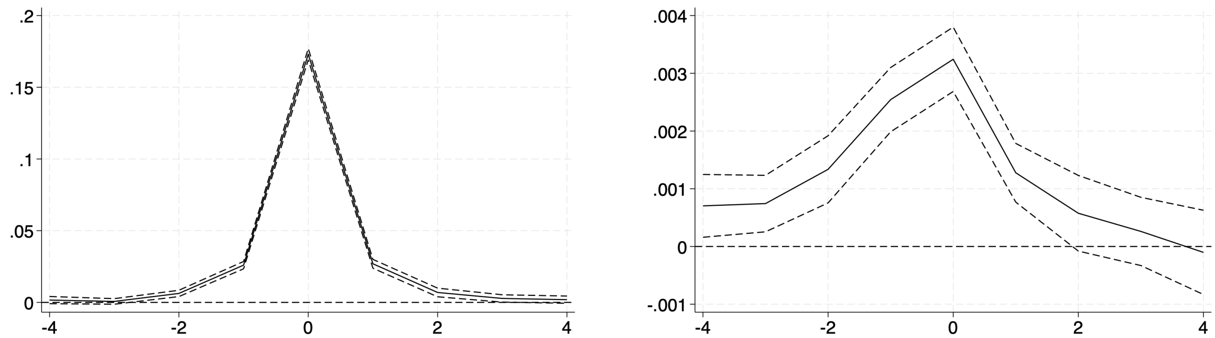
A.5 Innovation and Investment Spikes

This appendix contains four additional results about the relationship between R&D expenditures and investment spikes referenced in Section 6. First, Table A.7 Columns (1), (3), and (4) show that the main coefficient estimates are robust to including different lag lengths H. Second, Table A.7 Column (2) shows that the result holds when spikes are defined as an investment rate of one standard deviation above the mean investment rate within sector s.[28] Third, Table A.7 Column (5) shows that the results hold when adding size, sales growth, and current assets to the control vector X_{jt}. Finally, Figure A.5 complements the regression results with an event-study analysis around an investment spike, showing that R&D-to-sales tends to increase prior to these spikes.

[28] With our baseline definition of investment spikes, their frequency is 23%, and the average size of an investment spike is 37%, similar to that in the Census sample in Cooper and Haltiwanger (2006)

Figure A.5: Event Study Analysis of Investment Spikes

(a) Investment rates (b) R&D-to-sales



Notes: This figure shows the dynamics of investment rates and R&D-to-sales around investment spike episodes. The figure reports the coefficients β_h from estimating $y_{jt} = \alpha_j + \alpha_{st} + \sum_{h=-4}^{4} \beta_h \mathbb{1}\{\frac{x_{jt+h}}{k_{jt+h}} \geq 0.2\} + \varepsilon_{jt}$, where y_{jt} denotes the investment rate ($\frac{x_{jt}}{k_{jt}}$) or R&D-to-sales ratio ($\frac{\mathrm{RD}_t}{\tilde{y}_t}$); α_j and α_{ts} firm and time by sector fixed effects; and ε_{jt} is a random error term. For variable definitions and descriptive statistics, see Appendix A.

B Additional Model Analysis: Theory

This appendix provides various details of the model analysis mentioned in the main text.

B.1 Detrending

This subsection characterizes the detrended version of the firm's problem. We guess and verify that all quantity variables and the real wage scale with $\widetilde{A}_t = (A_t Z_t)^{\frac{1}{1-\alpha}}$, where $A_t = (1+g_A)^t$ and $Z_t = \int z_{jt} dj$ as defined in the main text. The exceptions are (i) labor demand ℓ_{jt}, which is stationary, and (ii) idiosyncratic productivity z_{jt}, which scales with Z_t alone. Define the associated growth rates

$$1 + g_t \equiv \frac{\widetilde{A}_{t+1}}{\widetilde{A}_t} = [(1+g_A)(1+g_{Zt})]^{\frac{1}{1-\alpha}}, \qquad 1 + g_{Zt} \equiv \frac{Z_{t+1}}{Z_t}.$$

We will now show that we can write the firm's problem (8) in terms of detrended variables and these growth rates. Abusing notation, in this appendix we write $v_t(z,n)$ as the value function of a continuing firm (which is denoted $v_t^{\text{cont}}(z,n)$ in the main text). Therefore, the firm's undetrended problem (8) is

$$v_t(z,n) = \max_{k',i,b'} \; n - k' - \widetilde{A}_t \left(\frac{z}{Z_t}\right)^{\frac{1}{1-\alpha-\nu}} i + \frac{b'}{1+r_t} + \frac{1}{1+r_t}\mathbb{E}_t\left[\pi_d n' + (1-\pi_d) v_{t+1}(z',n')\right]$$

$$\text{s.t.} \quad d \equiv n - k' - \widetilde{A}_t \left(\frac{z}{Z_t}\right)^{\frac{1}{1-\alpha-\nu}} i + \frac{b'}{1+r_t} \geq 0,$$

$$i \geq 0, \qquad b' \leq \theta_t(z,i,k'), \tag{21}$$

where the law of motion for net worth is

$$n' = \pi_{t+1}(z',k') + (1-\delta)k' - b'. \tag{22}$$

To detrend this problem, first define the detrended variables

$$\widetilde{n} \equiv \frac{n}{\widetilde{A}_t}, \qquad \widetilde{z} \equiv \frac{z}{Z_t}, \qquad \widetilde{v}_t(z,n) \equiv \frac{v_t(z,n)}{\widetilde{A}_t},$$

and, for next period's choices,

$$\widetilde{k}' \equiv \frac{k'}{\widetilde{A}_{t+1}}, \qquad \widetilde{b}' \equiv \frac{b'}{\widetilde{A}_{t+1}}.$$

Hence, $k'/\widetilde{A}_t = (1+g_t)\widetilde{k}'$ and $b'/\widetilde{A}_t = (1+g_t)\widetilde{b}'$.

Divide both sides of the firm's Bellman equation (21) by $\widetilde{A}_t$ to get

$$\frac{v_t(z,n)}{\widetilde{A}_t} = \max_{k',i,b'} \; \widetilde{n} - (1+g_t)\widetilde{k}' - \widetilde{z}^{\frac{1}{1-\alpha-\nu}} i + \frac{(1+g_t)\widetilde{b}'}{1+r_t} + \frac{1}{1+r_t}\mathbb{E}_t\left[\pi_d \frac{n'}{\widetilde{A}_t} + (1-\pi_d)\frac{v_{t+1}(z',n')}{\widetilde{A}_t}\right].$$

Multiply the terms in the continuation value by $\frac{\widetilde{A}_{t+1}}{\widetilde{A}_{t+1}}$ and use the definition of g_t to arrive at

$$\widetilde{v}_t(z,n) = \max_{k',i,b'} \; \widetilde{n} - (1+g_t)\widetilde{k}' - \widetilde{z}^{\frac{1}{1-\alpha-\nu}} i + \frac{(1+g_t)\widetilde{b}'}{1+r_t} + \frac{1+g_t}{1+r_t}\mathbb{E}_t\left[\pi_d \widetilde{n}' + (1-\pi_d)\widetilde{v}_{t+1}(z',n')\right].$$

Since the Bellman operator defined above only involves detrended variables $\widetilde{z}$ and $\widetilde{n}$, by the contraction mapping theorem we have $\widetilde{v}_t(z,n) = \widetilde{v}_t(\widetilde{z},\widetilde{n})$.

Dividing the no-equity-issuance constraint by $\widetilde{A}_t$ immediately gives the detrended version with detrended dividend constraint

$$\widetilde{n} - (1+g_t)\widetilde{k}' - \widetilde{z}^{\frac{1}{1-\alpha-\nu}} i + \frac{(1+g_t)\widetilde{b}'}{1+r_t} \geq 0.$$

To detrend the law of motion for net worth, first consider operating profits $\pi_t(z,k)$. We have

$$\begin{aligned}
\frac{\pi_{t+1}(z',k')}{\widetilde{A}_{t+1}} &= \widehat{\nu}\frac{(A_{t+1}z')^{\frac{1}{1-\nu}}(k')^{\frac{\alpha}{1-\nu}} w_{t+1}^{-\frac{\nu}{1-\nu}}}{\widetilde{A}_{t+1}} \\
\implies \frac{\pi_{t+1}(z',k')}{\widetilde{A}_{t+1}} &= \widehat{\nu}\left(\frac{k'}{\widetilde{A}_{t+1}}\right)^{\frac{\alpha}{1-\nu}} \left(\frac{w_{t+1}}{\widetilde{A}_{t+1}}\right)^{-\frac{\nu}{1-\nu}} \frac{(A_{t+1}z')^{\frac{1}{1-\nu}}}{\widetilde{A}_{t+1}^{1-\frac{\alpha}{1-\nu}+\frac{\nu}{1-\nu}}}.
\end{aligned}$$

Now note that $1 - \frac{\alpha}{1-\nu} + \frac{\nu}{1-\nu} = \frac{1-\nu-\alpha+\nu}{1-\nu} = \frac{1-\alpha}{1-\nu}$, so we have

$$\begin{aligned}
\frac{\pi_{t+1}(z',k')}{\widetilde{A}_{t+1}} &= \widehat{\nu}\left(\frac{k'}{\widetilde{A}_{t+1}}\right)^{\frac{\alpha}{1-\nu}} \left(\frac{w_{t+1}}{\widetilde{A}_{t+1}}\right)^{-\frac{\nu}{1-\nu}} \left(\frac{A_{t+1}z'}{\widetilde{A}_{t+1}^{1-\alpha}}\right)^{\frac{1}{1-\nu}} \\
\implies \frac{\pi_{t+1}(z',k')}{\widetilde{A}_{t+1}} &= \widehat{\nu}\left(\frac{k'}{\widetilde{A}_{t+1}}\right)^{\frac{\alpha}{1-\nu}} \left(\frac{w_{t+1}}{\widetilde{A}_{t+1}}\right)^{-\frac{\nu}{1-\nu}} \left(\frac{A_{t+1}z'}{A_{t+1}Z_{t+1}}\right)^{\frac{1}{1-\nu}} \\
\implies \frac{\pi_{t+1}(z',k')}{\widetilde{A}_{t+1}} &= \widehat{\nu}\left(\widetilde{k}'\right)^{\frac{\alpha}{1-\nu}} (\widetilde{w}_{t+1})^{-\frac{\nu}{1-\nu}} (\widetilde{z}')^{\frac{1}{1-\nu}} \equiv \widetilde{\pi}_{t+1}(\widetilde{z}',\widetilde{k}').
\end{aligned}$$

From here, it is trivial to see

$$\widetilde{n}' = \widetilde{\pi}_{t+1}(\widetilde{z}',\widetilde{k}') + (1-\delta)\widetilde{k}' - \widetilde{b}'.$$

Next, consider the law of motion for detrended productivity. In the case of a successful innovation, we have

$$\begin{aligned}
\frac{z'}{Z_{t+1}} &= \frac{z}{Z_t}\frac{Z_t}{Z_{t+1}} e^{\Delta} Z_t^{-\phi} \\
\implies \widetilde{z}' &= \frac{\widetilde{z}}{1+g_{Zt}} e^{\Delta} Z_t^{-\phi},
\end{aligned}$$

using $1 + g_{Zt} = \frac{Z_{t+1}}{Z_t}$. Similarly, in the case where there's no successful innovation, we have

$$\widetilde{z}' = \frac{\widetilde{z}}{1 + g_{Zt}} Z_t^{-\phi}.$$

Putting these two cases together, detrended productivity follows:

$$\log \widetilde{z}' = \begin{Bmatrix} -\log(1+g_{Zt}) + \log \widetilde{z} + \Delta - \phi \log Z_t \text{ with probability } \eta(i) \\ -\log(1+g_{Zt}) + \log \widetilde{z} - \phi \log Z_t \text{ with probability } 1 - \eta(i) \end{Bmatrix}.$$

Finally, the borrowing constraint is consistent with the detrending if there exists a detrended borrowing-capacity function $\widetilde{\theta}_t$ such that

$$\widetilde{\theta}_t(\widetilde{z}, i, \widetilde{k}') \equiv \frac{\theta_t(Z_t \widetilde{z}, i, \widetilde{A}_{t+1} \widetilde{k}')}{\widetilde{A}_{t+1}}. \tag{23}$$

In that case, the undetrended constraint $b' \leq \theta_t(z, i, k')$ is equivalent to

$$\widetilde{b}' \leq \widetilde{\theta}_t(\widetilde{z}, i, \widetilde{k}').$$

All borrowing-capacity specifications considered in the paper are imposed in a way that satisfies (23). For example, the baseline collateral constraint $\theta_t(z, i, k') = \theta k'$ becomes $\widetilde{\theta}_t(\widetilde{z}, i, \widetilde{k}') = \theta \widetilde{k}'$.

Putting these pieces together, we can write the firm's problem entirely in detrended terms. To simplify notation, we drop tildes from all detrended variables below. Thus, z denotes idiosyncratic productivity relative to Z_t, and all variables other than labor and innovation intensity are expressed relative to $\widetilde{A}_t$. The detrended problem is

$$\begin{aligned} v_t(z, n) = \max_{k', i, b'} \quad & n - (1+g_t)k' - z^{\frac{1}{1-\alpha-\nu}} i + \frac{(1+g_t)b'}{1+r_t} \\ & + \frac{1+g_t}{1+r_t} \mathbb{E}_t \left[\pi_d n' + (1-\pi_d) v_{t+1}(z', n') \right] \\ \text{s.t.} \quad & n - (1+g_t)k' - z^{\frac{1}{1-\alpha-\nu}} i + \frac{(1+g_t)b'}{1+r_t} \geq 0, \\ & i \geq 0, \qquad b' \leq \theta_t(z, i, k'). \end{aligned} \tag{24}$$

The law of motion for detrended net worth is

$$n' = \pi_{t+1}(z', k') + (1 - \delta)k' - b' \tag{25}$$

with

$$\pi_t(z, k) = \max_{\ell} zk^{\alpha}\ell^{\nu} - w_t\ell = \widehat{\nu}\, z^{\frac{1}{1-\nu}} k^{\frac{\alpha}{1-\nu}} w_t^{-\frac{\nu}{1-\nu}}, \tag{26}$$

and detrended productivity evolves according to

$$\log z' = \begin{cases} \log z - \log(1 + g_{Zt}) + \Delta - \phi \log Z_t & \text{with probability } \eta(i), \\ \log z - \log(1 + g_{Zt}) - \phi \log Z_t & \text{with probability } 1 - \eta(i). \end{cases} \tag{27}$$

B.2 Solving Firm's Problem

We solve the firm's problem in three steps. First, we set up the Lagrangian and take first-order conditions. Second, we use those conditions to derive the partition of the state space from the first part of Proposition 1. Finally, we un-detrend the conditions to get the equations displayed in the second part of Proposition 1.

First-Order Conditions The Lagrangian associated with the detrended Bellman equation (24) is

$$\begin{aligned} \mathcal{L} = &(1 + \lambda_t(z, n)) \left[n - (1 + g_t)k' - z^{\frac{1}{1-\alpha-\nu}} i + \frac{(1 + g_t)b'}{1 + r_t} \right] \\ &+ (1 + g_t)\mu_t(z, n) \left[\theta_t(z, i, k') - b' \right] + \chi_t(z, n) i \\ &+ \frac{1 + g_t}{1 + r_t} \mathbb{E}_t \left[\pi_d n' + (1 - \pi_d) v_{t+1}(z', n') \right], \end{aligned} \tag{28}$$

where $\lambda_t(z, n)$ is the multiplier on the non-negativity constraint on dividends, $(1 + g_t)\mu_t(z, n)$ is the multiplier on the borrowing constraint, and $\chi_t(z, n)$ is the multiplier on the non-negativity constraint on innovation.

The first-order condition for borrowing b' is

$$0 = (1 + \lambda_t(z, n))\frac{1 + g_t}{1 + r_t} - (1 + g_t)\mu_t(z, n) + \frac{1 + g_t}{1 + r_t}\mathbb{E}_t\left[(\pi_d + (1 - \pi_d)v_{2,t+1}(z', n'))\frac{\partial n'}{\partial b'}\right].$$

Using $\partial n'/\partial b' = -1$ and multiplying by $(1 + r_t)/(1 + g_t)$ gives

$$1 + \lambda_t(z, n) = (1 + r_t)\mu_t(z, n) + \mathbb{E}_t\left[\pi_d + (1 - \pi_d)v_{2,t+1}(z', n')\right].$$

The envelope condition is

$$v_{2,t}(z, n) = 1 + \lambda_t(z, n). \tag{29}$$

Using (29), subtracting one from both sides, and simplifying yields

$$\lambda_t(z, n) = (1 + r_t)\mu_t(z, n) + (1 - \pi_d)\mathbb{E}_t\left[\lambda_{t+1}(z', n')\right]. \tag{30}$$

Thus, the financial wedge $\lambda_t(z, n)$ is the expected value of the current and future multipliers on the borrowing constraint, accounting for exit.

The first-order condition for capital accumulation k' is

$$0 = -(1 + g_t)(1 + \lambda_t(z, n)) + (1 + g_t)\mu_t(z, n)\theta_{3,t}(z, i, k') + \frac{1 + g_t}{1 + r_t}\mathbb{E}_t\left[(\pi_d + (1 - \pi_d)v_{2,t+1}(z', n'))\frac{\partial n'}{\partial k'}\right],$$

where $\theta_{3,t}$ denotes the derivative of θ_t with respect to k'. Since

$$\frac{\partial n'}{\partial k'} = \pi_{2,t+1}(z', k') + 1 - \delta,$$

and $v_{2,t+1}(z', n') = 1 + \lambda_{t+1}(z', n')$, this condition becomes

$$1 + \lambda_t(z, n) = \frac{1}{1 + r_t}\mathbb{E}_t\left[(\pi_{2,t+1}(z', k') + 1 - \delta)\left(1 + (1 - \pi_d)\lambda_{t+1}(z', n')\right)\right] + \mu_t(z, n)\theta_{3,t}(z, i, k'). \tag{31}$$

The first-order condition for innovation i is

$$0 = -z^{\frac{1}{1-\alpha-\nu}}(1+\lambda_t(z,n)) + (1+g_t)\mu_t(z,n)\theta_{2,t}(z,i,k') + \chi_t(z,n)$$
$$+ \frac{1+g_t}{1+r_t}\frac{\partial}{\partial i}\mathbb{E}_t\left[\mathcal{V}_{t+1}(z',n')\right], \tag{32}$$

where $\theta_{2,t}$ denotes the derivative of θ_t with respect to i and $\mathcal{V}_{t+1}(z',n') \equiv \pi_d n' + (1-\pi_d)v_{t+1}(z',n')$. Innovation affects the continuation term by changing the probability of a successful innovation. Let $\iota \in \{0,1\}$ denote the realization of a successful innovation. Then

$$\frac{\partial}{\partial i}\mathbb{E}_t\left[\mathcal{V}_{t+1}(z',n')\right] = \eta'(i)\left(\mathbb{E}_t\left[\mathcal{V}_{t+1}(z',n') \mid \iota = 1\right] - \mathbb{E}_t\left[\mathcal{V}_{t+1}(z',n') \mid \iota = 0\right]\right). \tag{33}$$

Combining (32) and (33), and using the complementary slackness condition for $\chi_t(z,n)$, gives

$$1+\lambda_t(z,n) \geq (1+g_t)\mu_t(z,n)\frac{\theta_{2,t}(z,i,k')}{z^{\frac{1}{1-\alpha-\nu}}}$$
$$+ \frac{1+g_t}{1+r_t}\frac{\eta'(i)}{z^{\frac{1}{1-\alpha-\nu}}}\left(\mathbb{E}_t\left[\mathcal{V}_{t+1}(z',n') \mid \iota = 1\right] - \mathbb{E}_t\left[\mathcal{V}_{t+1}(z',n') \mid \iota = 0\right]\right), \tag{34}$$

with equality if $i > 0$.

To summarize, the firm's optimal decisions are characterized by (30), (31), and (34), together with the complementary slackness conditions

$$\mu_t(z,n)\left[\theta_t(z,i,k') - b'\right] = 0, \qquad \mu_t(z,n) \geq 0, \tag{35}$$

$$\lambda_t(z,n)\left[n - (1+g_t)k' - z^{\frac{1}{1-\alpha-\nu}}i + \frac{(1+g_t)b'}{1+r_t}\right] = 0, \qquad \lambda_t(z,n) \geq 0, \tag{36}$$

$$\chi_t(z,n)i = 0, \qquad \chi_t(z,n) \geq 0. \tag{37}$$

Partition of State Space We now use these conditions to derive the partition of the state space in the first part of Proposition 1.

Unconstrained firms. We define a financially unconstrained firm as one with $\lambda_t(z,n) = 0$.

Iterating (30) forward gives

$$\lambda_t(z,n) = \mathbb{E}_t\left[\sum_{s=0}^{\infty}(1-\pi_d)^s(1+r_{t+s})\mu_{t+s}(z_{t+s},n_{t+s})\right]. \tag{38}$$

Hence, a firm has $\lambda_t(z,n) = 0$ if and only if it has zero probability of facing a binding borrowing constraint in any current or future state. Being unconstrained is therefore an absorbing state. We guess and verify that the real policies of such firms are independent of net worth and denote them by $k_t^*(z)$, $i_t^*(z)$, and $b_t^*(z)$.

When $\lambda_t(z,n) = \mu_t(z,n) = 0$, the firm is indifferent across combinations of internal funds and debt that leave it financially unconstrained. Following Khan and Thomas (2013), we resolve this indeterminacy using the minimum savings policy, i.e. the largest debt position $b_t^*(z)$ that leaves the firm unconstrained with probability one. To characterize this policy, consider the dividends the firm would pay next period after choosing the unconstrained policies today. If the firm exits next period, dividends are

$$d_{t+1}^{\text{exit}}(z'|z) = \pi_{t+1}(z', k_t^*(z)) + (1-\delta)k_t^*(z) - b_t^*(z).$$

If the firm continues next period, dividends are

$$\begin{aligned} d_{t+1}^{\text{cont}}(z'|z) = {} & \pi_{t+1}(z', k_t^*(z)) + (1-\delta)k_t^*(z) - b_t^*(z) \\ & - (1+g_{t+1})k_{t+1}^*(z') - (z')^{\frac{1}{1-\alpha-\nu}} i_{t+1}^*(z') + \frac{(1+g_{t+1})b_{t+1}^*(z')}{1+r_{t+1}}. \end{aligned}$$

The minimum savings policy is the largest level of debt that satisfies the borrowing constraint today and guarantees non-negative dividends next period in all states:

$$b_t^*(z) = \min\left\{\begin{array}{l} \theta_t(z, i_t^*(z), k_t^*(z)), \\ \min\limits_{z'}\left\{\pi_{t+1}(z', k_t^*(z)) + (1-\delta)k_t^*(z)\right\}, \\ \min\limits_{z'}\left\{\begin{array}{c} \pi_{t+1}(z', k_t^*(z)) + (1-\delta)k_t^*(z) - (1+g_{t+1})k_{t+1}^*(z') \\ - (z')^{\frac{1}{1-\alpha-\nu}} i_{t+1}^*(z') + \dfrac{(1+g_{t+1})b_{t+1}^*(z')}{1+r_{t+1}} \end{array}\right\} \end{array}\right\}. \tag{39}$$

Under these unconstrained policy functions, we guess and verify that the value function is linearly separable in net worth. To see this, guess that $v_{t+1}(z', n') = n' + v^*_{t+1}(z')$ and substitute the unconstrained policies into the Bellman equation. The terms involving borrowing cancel, leaving

$$\begin{aligned} v^*_t(z) = &-(1+g_t)k^*_t(z) - z^{\frac{1}{1-\alpha-\nu}} i^*_t(z) \\ &+ \frac{1+g_t}{1+r_t}\mathbb{E}_t\left[\pi_{t+1}(z', k^*_t(z)) + (1-\delta)k^*_t(z) + (1-\pi_d)v^*_{t+1}(z')\right], \end{aligned} \tag{40}$$

which verifies the guess.

Given this characterization of the value function, the first-order conditions (31) and (34) become

$$1 = \frac{1}{1+r_t}\mathbb{E}_t\left[\pi_{2,t+1}(z', k^*_t(z)) + 1 - \delta\right], \tag{41}$$

and

$$1 \geq \frac{1+g_t}{1+r_t}\frac{\eta'(i^*_t(z))}{z^{\frac{1}{1-\alpha-\nu}}}\left(\mathbb{E}_t\left[n' + (1-\pi_d)v^*_{t+1}(z') \mid \iota = 1\right] - \mathbb{E}_t\left[n' + (1-\pi_d)v^*_{t+1}(z') \mid \iota = 0\right]\right), \tag{42}$$

with equality if $i^*_t(z) > 0$. These equations do not depend on current net worth n, verifying that the real decisions of unconstrained firms are independent of net worth.

Finally, the unconstrained policies are feasible if the firm can choose them without violating the no-equity-issuance constraint in the current period. This requires

$$n - (1+g_t)k^*_t(z) - z^{\frac{1}{1-\alpha-\nu}} i^*_t(z) + \frac{(1+g_t)b^*_t(z)}{1+r_t} \geq 0.$$

Equivalently, the firm is financially unconstrained if

$$n \geq \overline{n}_t(z) \equiv (1+g_t)k^*_t(z) + z^{\frac{1}{1-\alpha-\nu}} i^*_t(z) - \frac{(1+g_t)b^*_t(z)}{1+r_t}. \tag{43}$$

Constrained firms. We define constrained firms as those with $\lambda_t(z, n) > 0$, i.e. firms that face a positive probability of a binding borrowing constraint either in the current period or in some future state. Since $\lambda_t(z, n) > 0$, complementary slackness implies that their no-equity-issuance binds:

$$n - (1+g_t)k' - z^{\frac{1}{1-\alpha-\nu}} i + \frac{(1+g_t)b'}{1+r_t} = 0. \tag{44}$$

We divide constrained firms into two cases. *Potentially constrained* firms have $\mu_t(z,n) = 0$, so their borrowing constraint does not bind in the current period. *Currently constrained* firms have $\mu_t(z,n) > 0$, so their borrowing constraint binds in the current period.

Consider first potentially constrained firms. Let $k_t^p(z,n)$ and $i_t^p(z,n)$ denote the policies that solve the first-order conditions (30), (31), and (34) under the restriction $\mu_t(z,n) = 0$. Given these policies, the binding dividend constraint pins down borrowing:

$$b_t^p(z,n) = \frac{1+r_t}{1+g_t}\left[(1+g_t)k_t^p(z,n) + z^{\frac{1}{1-\alpha-\nu}} i_t^p(z,n) - n\right]. \tag{45}$$

These potentially constrained policies are feasible if $b_t^p(z,n) \leq \theta_t(z, i_t^p(z,n), k_t^p(z,n))$. Equivalently,

$$n \geq \underline{n}_t(z,n) \equiv (1+g_t)k_t^p(z,n) + z^{\frac{1}{1-\alpha-\nu}} i_t^p(z,n) - \frac{1+g_t}{1+r_t}\theta_t(z, i_t^p(z,n), k_t^p(z,n)). \tag{46}$$

Thus, for $n < \overline{n}_t(z)$, firms satisfying (46) are potentially constrained: their current borrowing constraint does not bind, but precautionary motives affect their decisions because they may be constrained in the future.

If instead $n < \underline{n}_t(z,n)$, the potentially constrained policies are infeasible, so the firm is currently constrained. In this case $\mu_t(z,n) > 0$, and the borrowing constraint binds:

$$b' = \theta_t(z, i, k').$$

Combining this with the binding dividend constraint gives

$$(1+g_t)k' + z^{\frac{1}{1-\alpha-\nu}} i = n + \frac{1+g_t}{1+r_t}\theta_t(z, i, k'). \tag{47}$$

Currently constrained firms solve the full system of first-order conditions (30), (31), and (34), together with (47).

This establishes the partition of the state space in Proposition 1: firms with $n \geq \overline{n}_t(z)$ are financially unconstrained; firms with $n \in [\underline{n}_t(z,n), \overline{n}_t(z))$ are potentially constrained; and firms with $n < \underline{n}_t(z,n)$ are currently constrained. The equations in Proposition 1 are the un-detrended versions of these equations.[29]

B.3 Decomposition of Aggregate TFP

Recall the definition of aggregate TFP from the main text:

$$\text{TFP}_t = \frac{Y_t}{K_t^\alpha L_t^\nu},$$

which implies that $Y_t = \text{TFP}_t K_t^\alpha L_t^\nu$ by construction. Plug in our firm-level production function to get

$$\begin{aligned} \text{TFP}_t &= \frac{Y_t}{K_t^\alpha L_t^\nu} && (48)\\ &= \frac{1}{K_t^\alpha L_t^\nu} \int A_t z_{jt} k_{jt}^\alpha \ell_{jt}^\nu dj && (49)\\ &= A_t Z_t \int \frac{z_{jt}}{Z_t} \left(\frac{k_{jt}}{K_t}\right)^\alpha \left(\frac{\ell_{jt}}{L_t}\right)^\nu dj && (50)\\ &= A_t Z_t \mathcal{M}_t, && (51) \end{aligned}$$

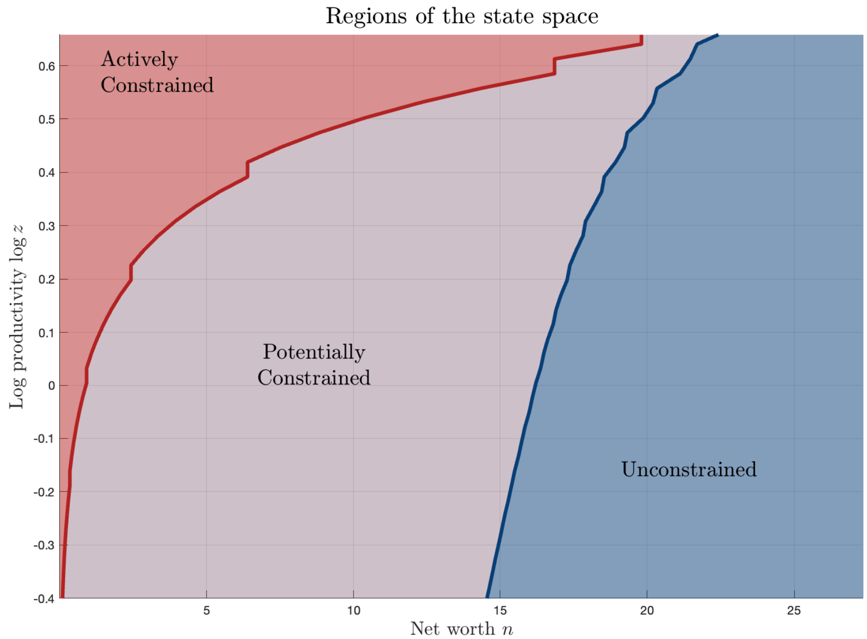
where $Z_t = \int z_{jt} dj$ is average productivity and $\mathcal{M}_t = \int \frac{z_{jt}}{Z_t} \left(\frac{k_{jt}}{K_t}\right)^\alpha \left(\frac{\ell_{jt}}{L_t}\right)^\nu dj$ is our measure of misallocation.

C Additional Model Analysis: Quantitative Results

This appendix provides additional quantitative results from the model referenced in the main text.

[29] It is possible that the first-order conditions have multiple solutions due to the complementarity between innovation and investment. However, in a simple version of the model, we have shown that, under our functional forms for $\eta(i)$, there is a wide range of parameters such that there is at most one interior solution to the FOCs. Other than this interior solution, the only other possibility is at the corner with zero innovation, which our algorithm takes into account. Consistent with this result, in the full calibrated model we have numerically found at most one interior solution to the FOCs as well. Results available upon request.

Figure C.1: Partition of the State Space



Notes: partition of the state space from Proposition 1. Net worth n and log productivity $\log z$ have been detrended following Appendix B.

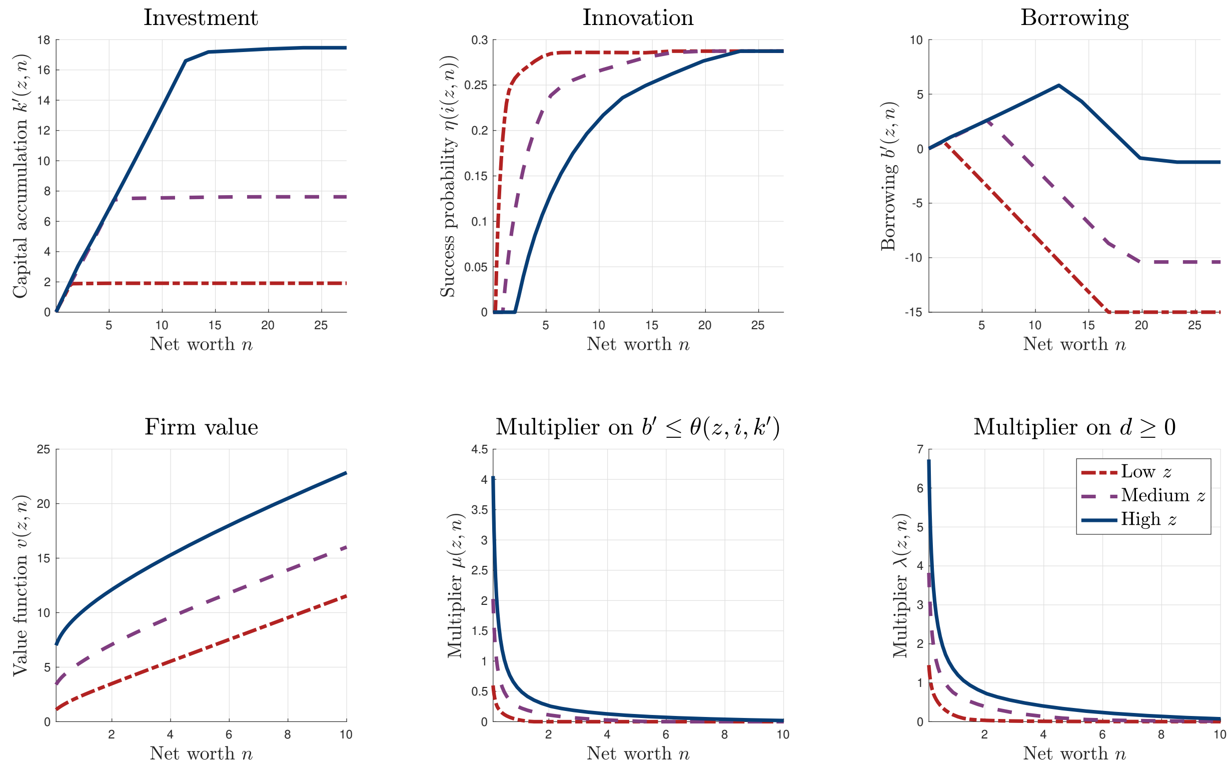
C.1 Validation of Calibrated BGP

We start with the validation of the calibrated BGP.

Sources of Firm Heterogeneity Figure C.1 visualizes the partition of the state space characterized in Proposition 1 in the initial BGP (plotted here for detrended productivity z and net worth n). The red isocurve implicitly defines the constrained cutoff $\underline{n}(z, n)$; firms above this curve are actively constrained. The level of net worth below which firms are constrained is increasing in productivity z because higher productivity firms have a higher optimal scale of capital $k^*(z)$ and therefore a greater incentive to borrow. The blue isocurve implicitly defines the unconstrained cutoff $\overline{n}(z)$; firms below this curve are financially unconstrained. Firms in between these two isocurves are potentially constrained.

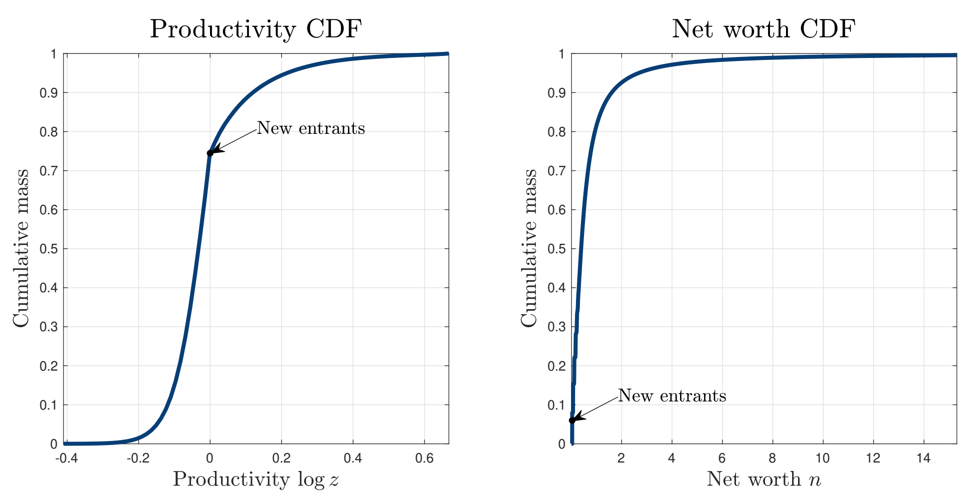
Figure C.2 plots firms' value functions and decision rules as a function of net worth n for different levels of productivity z (again, in detrended terms). Consistent with the pecking

FIGURE C.2: Decision Rules



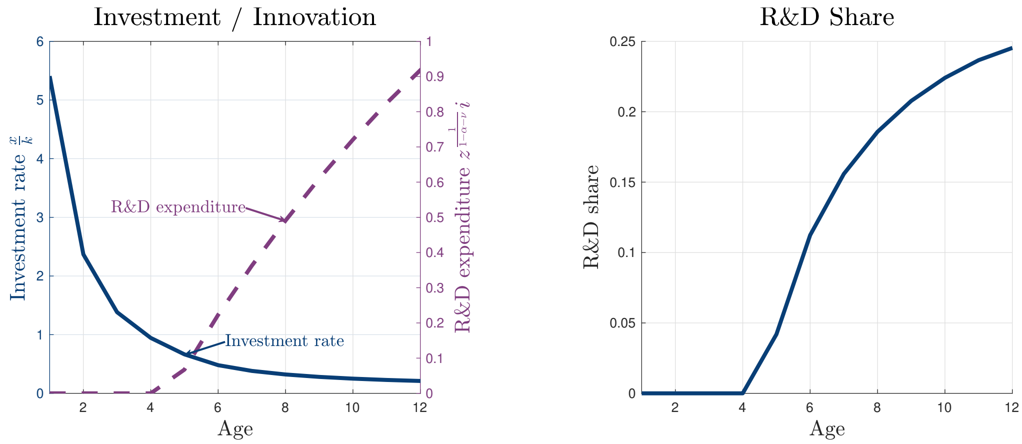
Notes: firm decision rules in the initial BGP. All variables have been detrended following Appendix B.

FIGURE C.3: Steady State CDFs



Notes: cumulative distribution functions of the marginal distributions of detrended log productivity $\log z$ (left panel) and detrended net worth n (right panel) in the stationary distribution of the calibrated model. All variables have been detrended following Appendix B.

FIGURE C.4: Sample Firm Lifecycle



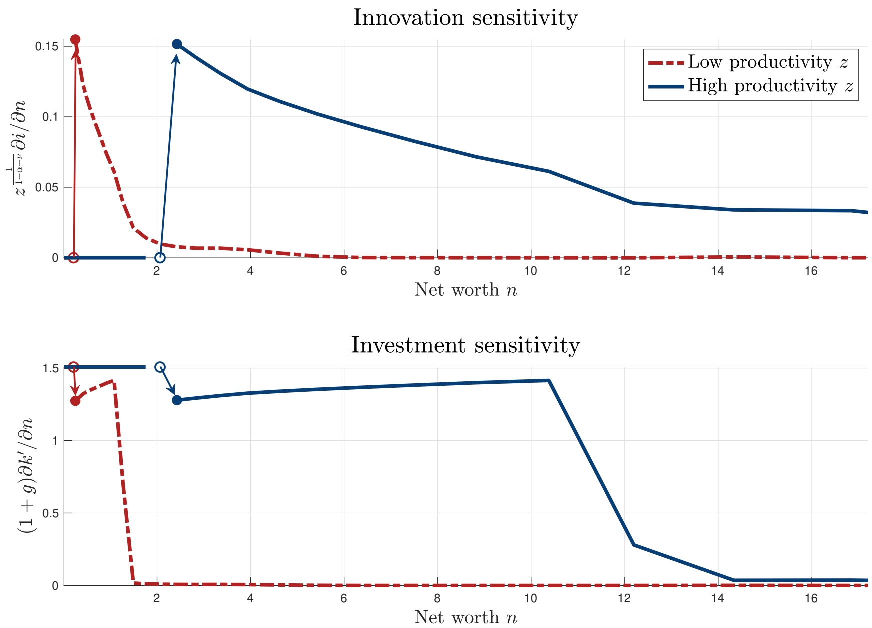
Notes: sample lifecycle profile for a firm without idiosyncratic shocks $\varepsilon_{jt} = 0$ for all j. Initially endowed with approximately average productivity and net worth among new entrants.

order of firm growth from Section 5, firms with low net worth spend all their available resources on investment and do not innovate. The level of net worth at which firms begin innovating is increasing in their productivity because higher-productivity firms have a higher marginal product of capital and, therefore, a higher opportunity cost of innovation. While constrained, firms accumulate debt until they reach their optimal scale $k^*(z)$, at which point they use additional net worth to pay down their debt (and potentially engage in financial saving). Once firms become financially unconstrained, they adopt the minimum savings policy described in Proposition 1. Unconstrained firms' capital varies substantially, but all unconstrained firms have the same innovation rate because of how the cost of innovation is scaled by productivity. Figure C.3 plots the resulting CDFs of the stationary distribution of productivity and net worth.

Figure C.4 plots a sample lifecycle for a firm that enters the economy at time $t = 0$. In order to highlight the role of innovation, we assume that the firm has a higher initial level of productivity z_0 than in the calibrated model. In its first years of life, the firm has a very high investment rate and does not innovate. As the firm ages, it exhausts its marginal product of capital, reducing its investment rate and increasing its innovation rate. These dynamics are consistent with the descriptive evidence from Figure 1 in the main text.

Figure C.5 plots the "cash flow sensitivities" of investment and innovation, defined as

Figure C.5: Cash Flow Sensitivities



Notes: cash flow sensitivities computed as $\frac{\partial(1+g^*)k'(z,n)}{\partial n}$ and $\frac{\partial z^{\frac{1}{1-\alpha-\nu}} i(z,n)}{\partial n}$. Derivatives computed using finite differences.

$\frac{\partial k'(z,n)}{\partial n}$ and $\frac{\partial i(z,n)}{\partial n}$. Of course, unconstrained firms have sensitivities of zero because their decision rules are independent of net worth (see Figure C.2). Among constrained firms, those that do not innovate simply put all additional net worth toward investment. We can explicitly compute the resulting investment-cash flow sensitivity by differentiating the flow of funds constraint (11) with innovation $i(z,n) = 0$ and borrowing $b' = \theta k'$

$$k'(z,n) = n + \frac{\theta k'(z,n)}{1+r} \implies \frac{\partial k'(z,n)}{\partial n} = \left(1 - \frac{\theta}{1+r}\right)^{-1} \approx 1.5,$$

where the last approximation uses our calibrated values of $\theta = 0.35$ and $r = 0.04$. Since firms can lever up investment with borrowing, their investment-cash flow sensitivities are above one. Constrained firms with positive innovation have a smaller investment-cash flow sensitivity because they put some of the additional funds toward innovation as well. Quantitatively, Figure C.5 shows that the innovation-cash flow sensitivities are an order of magnitude smaller than the investment-cash flow sensitivities.

Table C.1
Untargeted Statistics

Free cash flow ratio			*Leverage*			*Innovation*		
	Data	Model		Data	Model		Data	Model
Frac > 0	0.82	0.84	Mean (targeted)	0.16	0.17	Mean RD/sales	0.13*	0.13
Mean	0.08	0.05	Median	0.17	0.33	Freq. of patents	0.21	0.22
Median	0.08	0.05	IQR	0.39	0.29	Inn. elasticity		0.74
IQR	0.11	0.12	SD	0.34	0.26			

Notes: cross-sectional statistics from stationary distribution of firms vs. the data. Empirical statistics drawn from Compustat data described in Appendix A. Model statistics drawn from artificial Compustat sample described in main text. In the data, we define "free cash flow ratio" as the sum of EBITDA and research and development expense, minus income taxes and capital expenditures, divided by lagged total assets. In the model, we define the free cash flow ratio as the analogous object $\frac{\pi(z,k)-(k'-(1-\delta)k)}{k-\min\{b,0\}}$. "Leverage" is net leverage, as in the main text. "Mean R&D to sales" corresponds to R&D expenditures for firms that report positive R&D. The empirical value in Compustat equals 0.06, which we multiply by 2 in order to compare to the model. This adjustment reflects the fact that sales in the model correspond to value added, while in the data they correspond to gross sales. We do not have observations of intermediate inputs in the data, so multiplying by 2 is equivalent to assuming an intermediates share of 1/2 (broadly consistent with aggregate statistics). For details on variable definitions in the data, see Appendix A.

Untargeted Statistics Table C.1 compares untargeted statistics in the model to their empirical counterparts as a validation of the calibration. The first set of statistics concerns the distribution of free cash flow across firms. Conceptually, free cash flow measures internal resources net of investment expenditures: if free cash flow is positive, the firm can finance its investment without relying on costly external finance. The natural model analog is $\pi_t(z,k) - \widetilde{A}_t\,(z/Z_t)^{\frac{1}{1-\alpha-\nu}}\,i_t(z,n) - [k_t'(z,n) - (1-\delta)k]$. Using the flow-of-funds constraint, this object equals $d + b - b_t'(z,n)/(1+r_t)$, the firm's net payments to external investors. In the data, however, this ideal object is difficult to measure because R&D expenditures are expensed and therefore already subtracted from EBITDA. Since R&D expenditures are measured with substantial error, using reported R&D to construct free cash flow would create erroneous discrepancies between the model and the data. We therefore define free cash flow before R&D expenditures in both the model and the data. In the model, this object is $\pi_t(z,k) - [k_t'(z,n) - (1-\delta)k]$, while in the data we add reported R&D expenditures back into reported $EBITDA$. We also net out income taxes from the data, which are absent from the model (for details, see Appendix A.1).

The first panel of Table C.1 shows that the distribution of free cash flow is similar in the model and the data. Free cash flow is positive for most firms, indicating that most firms can finance their investment expenditures internally. On average, free cash flow is about 5% in the model and 8% in the data, with a similar dispersion. Taken together, these results show that the model does not rely on firms requiring an unrealistic amount of external finance. Instead, financial constraints have aggregate effects because they bind for a subset of firms, even though they do not bind for the typical firm in the sample. Moreover, firms with positive free cash flow can still be affected by financial frictions because they must also finance innovation expenditures and because potentially constrained firms have precautionary motives.

As further validation of our model, the second panel of Table C.1 compares the distribution of net leverage in the model and the data. Although the calibration targets mean leverage, it does not target the dispersion of leverage across firms. The model nevertheless generates a similar amount of dispersion, though somewhat less than in the data. This difference suggests that additional sources of leverage heterogeneity, which we abstract from in the model, may also be quantitatively relevant.

The third panel of Table C.1 reports untargeted statistics related to the innovation technology. First, to validate firms' incentives to spend on innovation inputs, we compare average R&D-to-sales among firms with positive R&D expenditures, which helps reduce measurement error from under-reported R&D. Second, the model closely matches the frequency of successful innovation, measured by granted patents in the data and realized innovation success in the model. Finally, we report the average elasticity of the success probability $\eta(i)$ with respect to innovation intensity across firms, as discussed in the main text.

Firm Growth by Size and Age Most of our analysis focuses on the composition of firm growth, i.e. how firms shift between capital investment and innovation as they grow. We now show that the model is also consistent with basic patterns of overall firm growth over the life cycle. To do so, we estimate two sets of regressions in both the data and the artificial Compustat sample generated by the model. First, we estimate

$$o_{jt} = \alpha_j + \gamma \log n_{jt} + \epsilon_{jt},$$

Table C.2
Firm Size and Growth, Model vs. Data

	Δ log employment (1)	log employment (2)
Log net worth (standardized)		
Data	−0.052	0.850
	(0.006)	(0.040)
Model	−0.032	0.647
Firm Age		
Data	−0.004	0.035
	(0.000)	(0.003)
Model	−0.002	0.044

Notes: top panel estimates $o_{jt} = \alpha_j + \gamma \log n_{jt} + \epsilon_{jt}$ where $\log n_{jt}$ is log net worth, standardized over the entire sample. Bottom panel estimates $o_{jt} = \alpha_j + \gamma \text{age}_{jt} + \epsilon_{jt}$ where age_{jt} is firm age. The outcomes are o_{jt} = the log-change in employment in column (1) and the log of employment in column (2). Data estimates are from our Compustat sample, and model estimates are from the artificial Compustat sample described in the main text.

where o_{jt} is either the log change in employment or the log of employment, α_j is a firm fixed effect, and $\log n_{jt}$ is log net worth standardized over the whole sample. The top panel of Table C.2 shows that, in both the model and the data, employment growth declines with net worth. The model generates this pattern because low net worth firms have high marginal products of capital. These dynamics generate a positive relationship between net worth and employment, also consistent with the data.

Second, to study the life cycle of growth, we estimate a similar specification with firm age:

$$o_{jt} = \alpha_j + \gamma \text{age}_{jt} + \epsilon_{jt}.$$

The bottom panel of Table C.2 shows that, in both the model and the data, firm growth rates decline with age. Again, this occurs in the model because young firms have a low capital stock. The model matches the resulting size-age relationship within firms particularly well.

C.2 Role of Heterogeneity and Prices

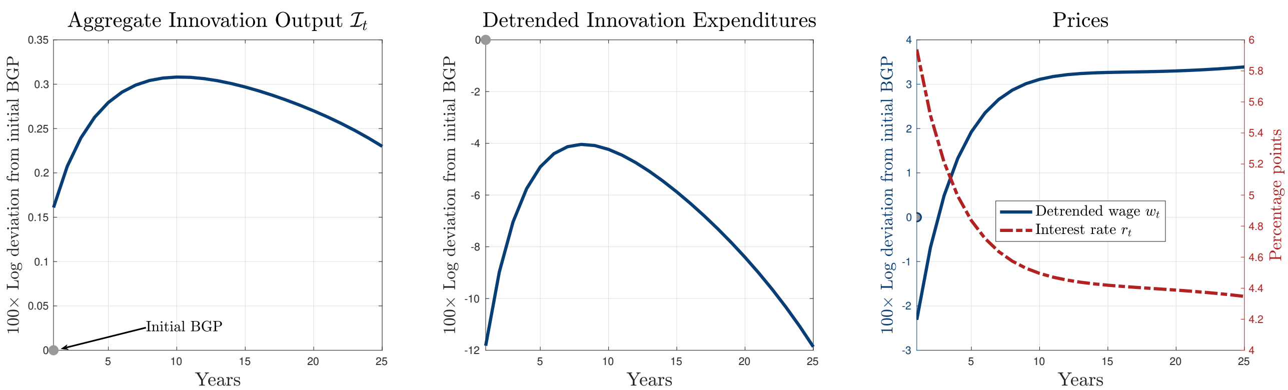
Table C.3 expands on the role of firm heterogeneity and equilibrium price movements in the response to removing financial frictions. We sort firms into quintiles based on their innovation

Table C.3
Understanding Reallocation

Quintile	Initial $\eta(i(z,n))$	Change in $\eta(i_0^*(z,n))$	Change in expenditures
Q1	0.00	+ 0.17	+ 0.04
Q2	0.09	+ 0.08	+0.02
Q3	0.21	− 0.04	−0.01
Q4	0.23	− 0.05	−0.01
Q5	0.23	− 0.06	−0.06

Notes: firms sorted into quintiles by innovation success probability $\eta(i_0(z,n))$ in the initial BGP. "Change in $\eta(i(z,n))$" is the average change in innovation output across firms in each quintile after removing financial frictions in period $t = 0$ compared to the initial BGP. "Change in expenditures" is the average change in innovation expenditures $A_0(z/Z_0)^{\frac{1}{1-\alpha-\nu}} i_0^*(z,n)$ in period $t = 0$ compared to the initial BGP.

Figure C.6: Role of Heterogeneity and Prices



Notes: transition paths after removing financial frictions once-and-for-all at $t = 0$, starting from the initial BGP. Left panel plots the log-change in the aggregate innovation index $\mathcal{I}_t$ in log-deviations from the initial BGP. Middle panel plots the log-change in aggregate innovation expenditures, again in log-deviation from the initial BGP and detrended relative to $\widetilde{A}_t$. Right panel plots the paths of the real wage w_t relative to $\widetilde{A}_t$ in log-deviation from the initial BGP (left y axis) and the level of the interest rate r_t (right y axis).

intensity $i(z,n)$ along the initial BGP. When financial frictions are removed, all firms choose the same probability of success, which is $\eta(i_0^*(z)) = 0.17$ in period $t = 0$. The first two columns of the table show that this convergence to the frictionless policy involves substantial reallocation of innovation across firms: firms with initially low innovation intensity increase their probability of success, while firms with initially high innovation intensity reduce it.

The right panel of Figure C.6 shows that the decline in innovation among initially high-intensity firms is driven by equilibrium price movements. Removing financial frictions raises

Table C.4
Sensitivity Analysis

	Pecking Order Coeff.	PV of TFP Gains
Baseline	0.10	5.57
Higher $\eta'(0)$	0.10	3.31
Higher η_1	0.10	4.96
Higher θ	0.11	4.72
Higher k_0	0.10	5.28
Higher $\mathbb{E}[z_0]$	0.11	4.25
Higher $\sigma(z_0)$	0.10	5.15

Notes: Sensitivity analysis when perturbing one parameter at a time relative to the baseline calibration. "Higher $\eta'(0)$" sets η_0 such that $\eta'(0)$ is 25% above baseline. "Higher η_1" sets η_1 to be 25% above baseline. "Higher θ" sets the collateral parameter θ to be 25% above its baseline. "Higher k_0" sets the initial capital stock, relative to average capital in the economy, to be 25% above baseline. "$\mathbb{E}[z_0]$" increases initial productivity of new entrants to be 0.01 rather than 0. "Higher $\sigma(z_0)$" assumes distribution of log initial productivity to be normally distributed with mean 0 and standard deviation $0.5 \times \Delta$.

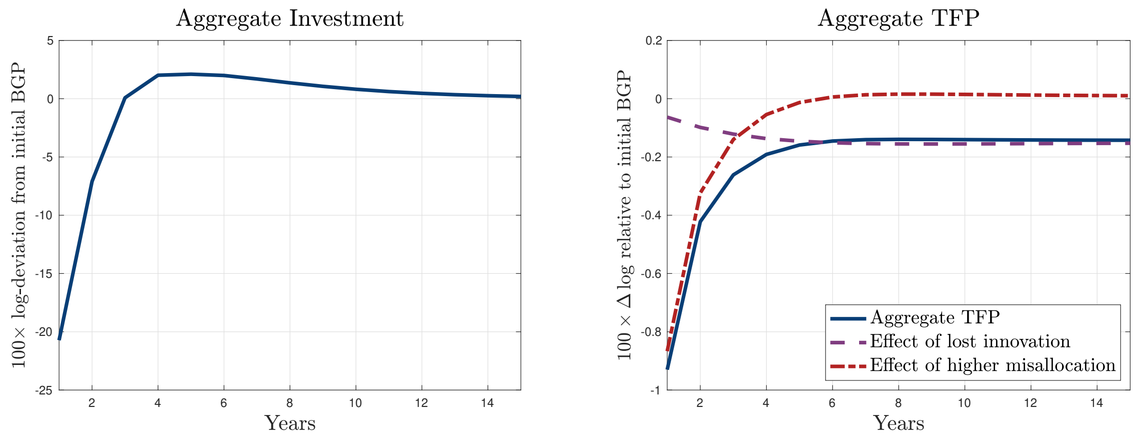
the real interest rate r_t, which reduces the present value of new ideas, and eventually raises the real wage w_t, which reduces future profits (and therefore the incentive to innovate as well). On net, the aggregate innovation index still increases, as shown in the left panel, because the increase in innovation among initially low-intensity firms more than offsets the decline among initially high-intensity firms. Aggregate innovation expenditures nevertheless fall, because innovation expenditures scale with firm productivity and therefore place greater weight on the initially high-productivity, innovation-intensive firms.

C.3 Sensitivity Analysis

Table C.4 reports sensitivity analysis of our main results with respect to key parameters in the model. We summarize the results using two statistics. First, to measure the strength of the pecking order of firm growth, we report the regression coefficient of the R&D share on log net worth from (1). Higher values indicate that firms with higher net worth tilt more strongly toward innovation relative to investment. Second, to measure the aggregate costs of financial frictions, we report the present value of aggregate TFP gains along the counterfactual transition path in which financial frictions are removed.

Table C.4 shows that our main results are robust across these alternative parameterizations: the pecking order remains present, and the TFP gains from removing financial

Figure C.7: Transition Paths Following Financial Shock θ_t



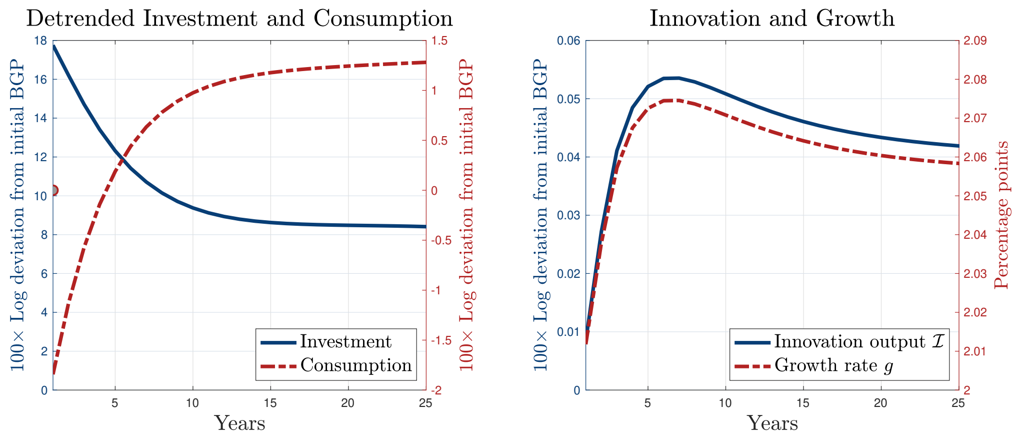
Notes: aggregate transition paths following an unexpected tightening of the collateral constraint θ_t. The shock is a 50% decline in θ_t at $t = 0$ which reverts to its steady state value with annual autocorrelation of 0.5. Left panel plots the path of aggregate investment in log-deviations from the initial BGP. Right panel plots the path of aggregate TFP, decomposed into contributions from misallocation ($\mathcal{M}_t$) and average productivity ($A_t Z_t$). Dashed black lines are the growth trajectory in the initial BGP.

frictions remain large and driven primarily by higher innovation. Increasing the return to innovation, either by raising η_0 or η_1, lowers the TFP gains because firms innovate more in the initial frictional allocation. Loosening financial constraints by increasing the collateral parameter θ naturally reduces the gains from removing them. Similarly, increasing the initial capital stock k_0 reduces the gains because firms enter the economy less constrained. Finally, increasing the initial productivity of new entrants z_0, or adding dispersion in initial productivity, also reduces the gains because some firms enter closer to their unconstrained scale.

C.4 Temporary Financial Shocks

Figure C.7 studies a temporary financial shock, modeled as a 50% decline in borrowing capacity θ_t at $t = 0$ that reverts with annual autocorrelation 0.5. The left panel shows that aggregate investment falls on impact, with the decline concentrated among constrained firms, and then rebounds as borrowing capacity recovers. Since the shock is temporary, the economy eventually returns to the same steady-state capital stock. Quantitatively, the decline in investment on impact roughly matches the magnitude of the decline in non-residential fixed

Figure C.8: Growth Effects of Investment Subsidy



Notes: transition paths after introducing a permanent investment subsidy $\tau^x = 0.05$ at $t = 0$, starting from the calibrated BGP with no subsidies. Left panel plots detrended investment X_t and detrended consumption C_t in log-deviations from the initial BGP. Right panel plots the aggregate innovation index $\mathcal{I}_t$ in log-deviations from the initial BGP (left axis) and the growth rate g_t in percentage points (right axis). The subsidy is financed by lump-sum taxes on households.

investment during the 2007-2009 financial crisis.

The right panel shows the corresponding path of aggregate TFP. As in Khan and Thomas (2013), TFP falls immediately because tighter financial constraints increase misallocation. As the shock dissipates, misallocation also returns to steady state. The shock also reduces innovation among constrained firms, which lowers the path of average productivity Z_t. However, this innovation channel builds slowly because changes in innovation take time to affect the distribution of firm productivity. As a result, the short-run TFP effects of temporary financial shocks operate primarily through misallocation, even though the reduction in innovation leaves a small permanent loss in Z_t in the fully endogenous growth version of the model.

C.5 Investment Subsidy

Figure C.8 plots the transition path following the introduction of a permanent investment subsidy, $\tau^x = 5\%$. The left panel shows that the subsidy raises investment immediately. Consumption initially falls because the economy devotes more resources to capital accumulation, but eventually rises as the larger capital stock expands output. The right panel shows that the investment subsidy also raises the aggregate innovation index, $\mathcal{I}_t$, and therefore the growth rate of the economy. The reason is that capital and ideas are complementary: by raising firms' capital stocks, the investment subsidy also raises the return to innovation. This mechanism contrasts with the standard neoclassical growth model, in which an investment subsidy can raise growth only temporarily. In that model, lower taxes on investment increase the capital stock, but diminishing marginal returns to capital imply a higher level of output rather than a permanently higher growth rate.