Diverging Paths: Productivity and the Financing Choices of Small Versus Large Firms

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Abstract

Why do small firms react to improved productivity by returning capital to investors, while large firms respond by raising more external financing? Using U.S. public firm data from 1971 to 2019, we find that a one–standard deviation increase in productivity reduces external financing by 3.3% of assets for small firms but increases it by 0.3% for large firms. We show that fixed costs of technology adoption can explain this pattern. Large firms finance profitable investment opportunities, whereas small firms avoid projects whose fixed costs cannot be covered. Causal evidence from exogenous variation in state R&D tax credits shows that an increase in R&D cost leads to a more negative correlation between external financing and productivity. A triple-interaction analysis further indicates that the divergence weakens as R&D cost increases, finding that R&D cost is a key driver of firm-size divergence.

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1 Introduction

How do firms adjust their financing decisions when productivity improves? The conventional answer is straightforward. Higher productivity increases the marginal return to capital, making external financing more attractive. Standard investment theory formalizes this idea through Q-theory (Hayashi, 1982). Financing-constraint models reinforce the idea as more productive firms appear safer to lenders (Fazzari et al., 1988; Almeida et al., 2004). This reasoning is so widely accepted that empirical studies use productivity shocks as instruments for financing capacity (Almeida and Campello, 2007), and policy makers assume that improving firm productivity will stimulate investment and growth (Romer, 1990).

We show that this conventional wisdom does not hold uniformly. Using U.S. public firms from 1971 to 2019, we document a sharp divergence in financing decisions. Large firms increase external financing when productivity improves. Small firms reduce it. A one–standard deviation increase in productivity reduces external financing by 3.3% of assets for small firms but increases it by 0.3% for large firms. Small firms return capital to investors precisely when standard theories predict they should raise more. The difference in external financing between the top and bottom firm-size quintiles is 3.6% of total assets.

We explain this puzzle using a monopolistic competition model in which fixed costs of technology adoption drive heterogeneous financing responses. Productivity gains are often accompanied by investment opportunities. Large firms spread fixed costs over a broad revenue base, making adoption profitable and motivating external finance to help cover the costs. Small firms face the same fixed costs on a smaller base. Unable to cover the fixed costs, the adoption is unprofitable. Instead, they distribute cash to investors. The mechanism generates smooth, size-dependent differences in financing behavior, contrasting with the discrete constrained/unconstrained view of much traditional analysis (Fazzari et al., 1988; Almeida and Campello, 2007).

To identify whether size divergence is driven by the fixed cost of technology upgrade, we exploit firm-level variation in the user cost of R&D. Specifically, we use the staggered introduction of state R&D tax credits between 1980 and 2007, following Wilson (2009); Bloom et al. (2013); Hombert and Matray (2018), to create exogenous variation in firm-level user cost of R&D. We find that an increase in R&D cost indeed leads to a more negative correlation between productivity and external financing, consistent with the mechanism in which R&D costs generate size divergence.

To further identify that the size dispersion in the productivity–external financing relationship is driven by R&D cost, we link the size-based pattern to the idea that large firms effectively face lower fixed costs of conducting R&D. If firm size is driven by variation in a firm's R&D cost, then when a firm's R&D cost increases, the more positive correlation between productivity and external financing for large firms should attenuate. In a regression framework that regresses external financing on the triple interaction of productivity, firm size, and R&D cost, we find that the coefficient on this interaction is negative. This result suggests that R&D cost could indeed drive the size divergence. Moreover, we find that when R&D cost increases, the positive relationship between productivity and external financing for top-quartile size firms changes from positive but insignificant to significantly positive, suggesting that R&D cost indeed could alter the size divergence.

The R&D cost channel we document is highly significant. A one–standard deviation increase in R&D cost leads to a 1% decrease in external financing as a share of assets, for a median productivity firm when productivity increases. A one–standard deviation change in R&D cost can explain 28% of this difference across firm sizes. This suggests that a 3.5–standard-deviation increase in R&D cost could fully account for the size divergence between large and small firms. The results are even stronger for higher-productivity firms, where a one–standard-deviation increase in R&D cost can explain approximately 45% of the difference across firm sizes. In this case, only a 2.2–standard-deviation increase in R&D cost would be sufficient to explain the entire size divergence.

To rule out the effect of non–R&D-related tax incentives, we exploit the empirical setting from Zwick and Mahon (2017), which examines how bonus depreciation—an accelerated schedule that allows firms to deduct the cost of investment purchases from taxable income more quickly—affects corporate investment. If our results were driven by general tax incentives such as accelerated depreciation, we should observe differential external financing responses between large and small firms when bonus depreciation changes. However, we find no differential external financing responses between large and small firms when bonus depreciation changes, suggesting that general tax policy such as bonus depreciation does not explain the size divergence.

Our findings make three main contributions. First, we document a robust new empirical regularity. It is the size-dependent financing responses to productivity shocks. The continuous transition across firm sizes and the negative response of small firms are difficult to reconcile with existing theories of such as market power, traditional financing constraints, or representative firm behavior. Second, we offer a theoretical explanation based on fixed adoption costs. Our mechanism explains both our main result and several related facts, including weak Q-theory tests (Bond and Van Reenen, 2007) and rising productivity dispersion (Autor et al., 2020; De Loecker et al., 2020; Kehrig and Vincent, 2021; Ayyagari et al., 2024). Using our estimates, we calculate that diverging financing responses explain about 18% of the increase in productivity dispersion across firms since 1970. Third, we draw direct policy implications. Small business credit subsidies are often justified by presuming that small firms faces serious financing constraints (Brown et al., 2020). Our results suggest instead that fixed adoption costs may often be the binding margin. If so, general credit subsidies may have little effect on actual firm investments.

1.1 Related Literature

Our paper connects to three strands of literature. (i) Theories of investment and financing. (ii) Empirical work on financing constraints and productivity. (iii) Studies of rising productivity dispersion.

First, we contribute to the literature on investment under uncertainty and financing frictions. Classical Q-theory predicts that higher productivity raises investment (Hayashi, 1982; Bond and Van Reenen, 2007). Much of the empirical work tests whether financing constraints affect this sensitivity (Fazzari et al., 1988; Kaplan and Zingales, 1997; Whited, 1992; Farre-Mensa and Ljungqvist, 2016). Structural models highlight how frictions interact with growth opportunities (Gomes, 2001; Hennessy and Whited, 2007; Bolton et al., 2011). Recent contributions emphasize heterogeneity. Belo et al. (2019, 2022) model time-varying financing costs and input frictions. Ottonello and Winberry (2020) study heterogeneous responses to monetary policy. We differ from these as we study fixed technology adoption costs as the crucial margin. Our model generates smooth size-dependent financing responses rather than a constrained/unconstrained split between firms.

Second, our empirical work builds on research linking firm-level productivity to financing. Almeida and Campello (2007) use productivity shocks as instruments for financing capacity. De Loecker et al. (2020) and Ackerberg et al. (2015) refine productivity measurement and document rising heterogeneity. We follow standard approaches based on Olley and Pakes (1996) and Blundell and Bond (2000). We show that the effect of productivity on financing depends systematically on firm scale. In contrast to prior work assuming directionally uniform responses to shocks, we document diverging responses.

Third, we contributes to the literature on rising productivity dispersion. Autor et al. (2020); De Loecker et al. (2020); Kehrig and Vincent (2021) show widening gaps between large and small firms. Whited and Zhao (2021) study the role of misallocation of finance. We identify an important complementary channel. The differening financing responses to productivity shocks amplify productivity differences across firms. Our estimates imply that this channel accounts for roughly 18% of the increase in dispersion since 1970.

Overall we build on established theories and measurement approaches. We provide a new mechanism in the scale-dependent adoption costs. This explains both the empirical divergence in financing responses and part of the broader rise in productivity dispersion.

The rest of the paper is organized as follows. Section 2 develops the theoretical framework. Section 3 describes our data and empirical strategy. Section 4 describes our empirical strategy. Section 5 presents the main empirical findings, including both the baseline divergence results and the investment channel effects. Causal evidence on the role of R&D cost is provided in Section 6. Section 7 discusses economic magnitudes. Section 8 concludes.

2 Theoretical Framework

We develop a model where productivity improvements create technology adoption opportunities with heterogeneous fixed costs. The idea is that firm scale determines whether adoption is profitable. That in turn generates divergent financing responses to productivity shocks.

2.1 Setup

Consider firms characterized by productivity a_i operating under monopolistic competition (Dixit and Stiglitz, 1977; Melitz, 2003). Each firm earns profits $\pi_i = \kappa a_i^{\sigma-1}$ where $\sigma > 1$ is the elasticity of substitution and κ captures market conditions.[1] A productivity-enhancing technology becomes available that multiplies output by factor $h > 1$ but requires fixed cost ϕ_i. We assume that firms of different sizes have different values of ϕ_i. Specifically, we assume that the fixed cost of innovation is a random variable. Larger firms tend to have smaller ϕ_i, and therefore have lower density in the upper region of the ϕ_i distribution.

The incremental profit from adoption is

$$\Delta\pi_i = \pi_i(h^{\sigma-1} - 1) = \kappa a_i^{\sigma-1}(h^{\sigma-1} - 1) \tag{1}$$

[1] In our monopolistic competition framework, $\kappa = \frac{1}{\sigma-1}w$, where σ is the elasticity of substitution and w is the unit cost.

Firms adopt the new technology if the net benefit exceeds zero

$$B_i = \Delta\pi_i - \phi_i - r \cdot \max(\phi_i - c_0, 0) \geq 0 \tag{2}$$

where c_0 represents internal funds and $r > 0$ is the external financing wedge reflecting information asymmetries and transaction costs.

This adoption condition defines a threshold $\bar{\phi}(a_i)$ such that firms adopt if and only if $\phi_i \leq \bar{\phi}(a_i)$. And $\partial\bar{\phi}(a_i)/\partial a_i > 0$, because more productive firms can justify higher fixed costs.

External financing follows directly from the adoption decision.

$$e_i = \begin{cases} \phi_i - c_0 & \text{if adopts}(\phi_i \leq \bar{\phi}(a_i)) \\ -(\kappa a_i^{\sigma-1} - c_0) & \text{if does not adopt}(\phi_i > \bar{\phi}(a_i)) \end{cases} \tag{3}$$

The external financing decision is jointly determined by the carrying cost of cash and the firm's need to maintain an optimal cash level. Non-adopters return internal funds to investors because, when productivity improves, they generate excess cash relative to their target. They return $(\kappa a_i^{\sigma-1} - c_0)$, since they anticipate profits of $\kappa a_i^{\sigma-1}$ and therefore return an amount sufficient to bring their cash holdings back to the optimal level c_0. Empirically, in this region, this behavior appears as a negative correlation between external financing and productivity. In contrast, adopters must raise external funds to finance their investment. A detailed timeline is provided in Appendix Appendix A.

2.2 Productivity-Financing Relationship

Because we assume that firms face a random fixed-cost distribution, they make financing decisions based on the expected distribution of their fixed cost of innovation. Note that firms of different sizes have different distributions of ϕ_i. Larger firms tend to have smaller ϕ_i, and therefore have lower density in the upper region of the ϕ_i distribution.

Expected external financing conditional on productivity is

$$E[e_i|a_i] = \underbrace{\int_0^{\bar{\phi}(a_i)} (\phi - c_0) f(\phi) d\phi}_{\text{adopt, raise external finance}} - \underbrace{(\kappa a_i^{\sigma-1} - c_0)[1 - F(\bar{\phi}(a_i))]}_{\text{not adopt, distribute cash to investors}} \tag{4}$$

where F is the cumulative distribution function of fixed costs, and f is the corresponding density. This expression captures two opposing forces. Adopters seek external financing (the positive term), while non-adopters return cash to investors (the negative term). The net effect depends on how the fixed-cost distribution interacts with firm scale. In the adopt region, external finance $\int_0^{\bar{\phi}(a_i)} (\phi - c_0) f(\phi)\, d\phi$ increases when a_i increases, because the adoption threshold $\bar{\phi}(a_i)$ rises with productivity. In the non-adopt region, two forces are present. First, $[1 - F(\bar{\phi}(a_i))]$ decreases as a_i increases, because the non-adoption region becomes smaller when productivity rises. Second, the term $\kappa a_i^{\sigma-1} - c_0$ increases with productivity, as the firm expects higher profits and therefore returns more cash due to the carrying cost of cash. Firm size determines the relative dominance of the adopt and non-adopt regions in the fixed-cost distribution, thereby generating systematic differences in the relationship between productivity and external finance.

2.3 Propositions

The main implications of our model are summarized as propositions. The proofs are in Appendix Appendix A.

Proposition 2.1 (Divergent Financing Responses). *For large firms that face a lower density of high fixed costs, an increase in productivity leads to an increase in external financing ($\frac{\partial E[e_i|a_i]}{\partial a_i} > 0$). For small firms that face a higher density of high fixed costs, an increase in productivity leads to a decrease in external financing ($\frac{\partial E[e_i|a_i]}{\partial a_i} < 0$).*

This result formalizes the core divergence in financing behavior. Small firms facing productivity gains still find technology adoption unprofitable because fixed costs outweigh incremental benefits. They therefore return excess internal funds to investors. Empirically, this shows up as a negative correlation between external finance and productivity. Larger firms can spread the same fixed costs across a broader revenue base, making adoption profitable. Consequently, they raise external capital to finance these investments. Empirically, this appears as a more positive correlation between external finance and productivity.

Proposition 2.2 (Continuous Size Variation). *The financing response $\frac{\partial E[e_i|a_i]}{\partial a_i}$ varies continuously across firm size.*

Many models have discrete financing constraints. Tests comparing constrained and unconstrained firms are based on this idea (Fazzari et al., 1988; Almeida and Campello, 2007). Unlike the traditional financing-constraint models, our framework generates smooth variation. Because scale economies increase continuously with firm size, financing responses evolve gradually across the size distribution. This means that empirical tests should detect a continuum of behavior rather than sharp breaks. This helps reconcile why previous empirical studies often fail to find clean constrained/unconstrained splits. Normally this is attributed to variation in other exogenous factors beyond the theory. Here is internal to the model.

Proposition 2.3 (Investment Channel). *Firms with* $\frac{\partial E[e_i|a_i]}{\partial a_i} > 0$ *invest more in productivity-enhancing activities than firms with* $\frac{\partial E[e_i|a_i]}{\partial a_i} < 0$.

In our model a positive financing response to productivity improvements shows that the firm is adopting new technology. External capital is raised to fund the fixed costs of adoption. The firm simultaneously increases real investment. A negative financing response implies that adoption is not viable, and the firm distributes cash instead. This establishes a direct link between financing flows and real investment outcomes. It also shows how financing decisions amplify or dampen the effect of productivity shocks.

Proposition 2.4 (Fixed Cost Heterogeneity). *For firms facing higher expected fixed costs, the divergence in external finance between large and small firms weakens.*

This proposition provides a key test for whether the diverging financing responses are indeed driven by differences in fixed costs of innovation. If the divergence arises from firm-level differences in innovation fixed costs, then in a higher fixed-cost setting productivity improvements are unlikely to justify adoption for either small or large firms. For smaller firms, the non-adoption region dominates because fixed costs frequently exceed the gains from upgrading. For larger firms, although they face lower expected fixed costs, sufficiently high realizations still make adoption unlikely. As a result, both small and large firms behave similarly in the non-adoption region, and the difference in external finance between them weakens.

Proposition 2.5 (Policy Implications). *Policies that reduce fixed costs* ϕ_i *generate larger changes in financing responses than policies that reduce variable costs or the financing wedge* r *by equivalent amounts.*

A general principal of economic policy making is that good policy should be directly targeted at the distortion or market failure that justifies the policy in the first place. This general idea also applies to financing policies. In our setting fixed costs are the key problem. That suggests directly targeting the fixed costs themselves, perhaps through an R&D subsidy. That will be relatively effective in altering adoption thresholds and financing behavior. More general financing subsidies for small firms do not address the problem. Instead of increasing investment, the subsidies might be simply passed-through to the small firm's owners due to the fixed cost mechanism in our model.

The model comparative statics provide further predictions. We focus on three of these. First is about financial development. Reductions in the financing wedge r increase the adoption threshold. That allows more firms to profitably adopt technology. It raises the productivity level at which expected external financing becomes positive.

Second is about technological progress. Increases in the productivity enhancement factor h raise incremental profits proportionally to $a_i^{\sigma-1}$. This causes high-productivity firms to benefit disproportionately. It therefore amplifies that financing differences across firm sizes.

Third is about internal funds. Increases in c_0 have offsetting effects. They directly reducing external financing needs. But they also relax adoption constraints. So the net effect depends on the fixed cost distribution.

2.4 Mechanism Identification

Given how central our topic is for corporate finance, there are a number of other perspectives suggested by the previous literature. It is therefore important to consider how we can distinguish our framework from high profile ideas in the literature.

Standard Q-theory (Hayashi, 1982; Bond and Van Reenen, 2007) naturally predicts uniform positive financing responses to productivity improvements. this is because the marginal return to capital improved. There should be larger effects for more productive firms. This contradicts our 2.1 which points to sharply different decisions according to firm size.

Traditional financing constraint theory (Fazzari et al., 1988) predicts smaller but positive responses for constrained firms. It does not predict the large negative financing responses predicted by our model.

Market power theory (De Loecker et al., 2020; Gutiérrez and Philippon, 2017) does not explain why any productive firms would reduce external financing. Market power should increase rather than decrease investment incentives.

Credit rationing theory (Stiglitz and Weiss, 1981) is directly founded on the discrete difference between constrained and unconstrained firms. This contradicts the continuous variation built directly in the model as in Proposition 2.2. Of course, in reality firms differ in various exogenous ways that go beyond that theory. As a result more continuous variation is normally seen in the data (Petersen and Rajan, 1994).

Our fixed cost mechanism distinctively predicts that a set of firms experiencing a productivity gain, react by reducing external financing. Presumably the standard versions of these other theories could be modified to embed our mechanism into a more enriched model. So our theory and evidence is pointing to a specific economic mechanism. It is not intended to test or reject these other well-established theories.

2.5 Model Limitations

Our framework is intentionally stylized. The assumption of monopolistic competition is convenient but it abstracts from richer market structures. The fixed-cost mechanism itself simplifies the variety of technology adoption processes. We model external finance through a single wedge. We believe that this fixed cost mechanism provides helpful insights into the diverging paths.

In reality financing frictions presumably vary across financing instruments and various institutions. We also abstract from many types of heterogeneity such as managerial quality, governance, alternative types of intangible capital, and so forth. Many of these might interact with adoption decisions. The benefit of the simplification is that it allow us to clarify the mechanism of scale-dependent fixed costs. Our model is intended as a parsimonious benchmark. It is not intended as a complete description of firm financing and investment decisions.

3 Data and Methodology

3.1 Sample Construction

We use firm-level data from the merged Compustat/CRSP Fundamentals Annual database covering 1971 to 2019. A number of sample restrictions are required to ensure consistency with prior corporate finance research. We begin with 326,248 firm-year observations and apply standard filters used in corporate finance research. We exclude financial firms (SIC 6000–6999) and regulated utilities (SIC 4900–4949) because regulation alters the connection between productivity and financing. We also drop non-U.S. firms, firms with missing accounting variables required for productivity estimation (sales, COGS, SGA, and total assets), firms with zero or missing assets, and single-year observations. After applying these restrictions, the final sample consists of 141,767 firm-year observations representing 13,847 unique firms between 1971 and 2019. See Appendix Appendix B for more details.

These restrictions improve comparability with other paper, but they may also introduce potential biases. Dropping single-year firms could over-represent more established firms with longer histories. Similarly, measurement error in productivity is presumably more likely for smaller firms with noisier financial reporting. Our main results are robust to alternative specifications. But the data cleaning steps should be kept in mind when interpreting the empirical evidence. The biases created in the cleaning process are likely to reduces rather than exaggerate the documented size-dependent financing responses. This means that our estimates may somewhat underestimate the true effects to a small extent.

Our main dependent variable is external financing, measured as the sum of net debt issuance and net equity issuance scaled by lagged assets, following Frank and Goyal (2009). Net debt issuance equals long-term debt issued minus long-term debt retired plus changes in current debt. Net equity issuance equals sales of stock minus repurchases. Productivity is the estimated residual from the production function regressions. Firm size is measured as lagged total assets (in constant 2019 dollars using the GDP deflator) and firms are sorted annually into quintiles based on size. Table 1 Panel A reports the summary statistics for firms in our main sample from 1971 to 2019. Table 1 Panel C reports the mean values of key characteristics for firms in different quintiles.

3.2 Productivity Estimation

We estimate firm-level productivity as residuals from production function regressions following De Loecker et al. (2020). Specifically, we regress log sales on inputs including cost of goods sold (COGS), selling, general and administrative expenses (SGA), and gross capital (PPEGT). Estimation is conducted separately for each Fama-French 48 industry and decade to allow for heterogeneous technologies across sectors and time.

We employ a control-function approach to address the simultaneity between inputs and productivity using Olley and Pakes (1996), following the main specification in Ackerberg et al. (2015). The resulting productivity measures show substantial and plausible variation across firms. Average coefficients on inputs are consistent with prior studies. COGS coefficients average 0.72, SGA 0.18, and capital 0.16, with an adjusted R^2 above 0.97 across 384 industry-decade regressions. Firm-level productivity is measured as,

$$a_{i,t} = \ln(\text{Sales}_{i,t}) - \alpha_C \ln(\text{COGS}_{i,t}) - \alpha_S \ln(\text{SGA}_{i,t}) - \alpha_{PPEGT} \ln(\text{PPEGT}_{i,t}) \tag{5}$$

. Appendix Table A2 provides more details. These values are well within the ranges reported in De Loecker et al. (2020) for U.S. manufacturing firms and in Olley and Pakes (1996) for plant-level productivity. For more details see Appendix Appendix C.

3.3 State-Level R&D Tax Credit and User Cost of R&D

Empirically, cross-firm variation in fixed costs of technology upgrade can be proxied by differences in R&D cost. Among firms of similar size, a lower R&D cost indicates that the initial fixed cost required for technology upgrading is smaller relative to firms with higher R&D costs. We use user cost of R&D to measure the fixed cost associated with technology adoption. We use Hall-Jorgensen formula for user cost of R&D. We first exploit the state-level variation in the user cost of R&D, which is defined as $\rho_{st} = \frac{1-D_{st}}{1-\tau_{st}}[r_t + \delta]$, where D_{st} is tax credit, τ_{st} is corporate tax credit, and r_t is, and δ is the depreciation rate of R&D. We follow Wilson (2009) in applying a fixed 15% depreciation rate for R&D. We also use their construction of the state-level R&D tax credit, which leverages the staggered rollout of these credits across states. Beginning in Minnesota in 1982, and extending through 2006, 32 states had adopted an R&D tax credit. Figure 1 illustrates the geographic distribution of state-level R&D tax credits. These credits reduce the after-tax cost of research and development. The policy variation is plausibly exogenous to individual firm financing decisions while directly affecting productivity through lower innovation costs. Literature such as Bloom et al. (2013) has demonstrated that changes in state R&D tax credit policies are largely exogenous and not driven by state-level economic conditions.

Firms are eligible for tax credits depending on where the R&D is conducted. We exploit this exogenous state-level variation in the user cost of R&D and compute a firm-level measure of the user cost of R&D, following the methodology used in Bloom et al. (2013) and Hombert and Matray (2018). Firm level user cost of R&D is defined as $\rho_{it} = \sum_s w_{ist}\rho_{st}$, where w_{ist} is the 10-year moving average of the location of firm's R&D activity using the location of its individual inventors, and ρ_{st} is state-level user cost of R&D. When analyzing firm-level user cost of R&D, our sample includes 39,942 firm-year observations from 1980 to 2007, for which the user cost of R&D measure is non-missing. Table 1 Panel B reports the summary statistics for firms in our R&D cost sample.

The variation of our measure of firm-level user cost of R&D is mainly coming from the exogenous variation of state-level variation in the user cost of R&D. This variable is commonly used in the literature as exogenous shock and instrument for firms R&D capital stock (Bloom et al. (2013), Hombert and Matray (2018)). The main concern is the historical location of inventors, as firms could endogenously choose where inventors are based based on other unobservable firm characteristics. This concern is less prominent in the prior literature, because the location of inventors—while potentially chosen to benefit from lower R&D costs—is not correlated with other variables that affect their outcomes of interest. However, in our setting, the endogenous location choice of inventors is more salient, as we aim to examine how firms' external financing decisions respond to productivity shocks differentially across firms with different R&D costs. Endogenous adjustments in inventor location could potentially be related to other firm characteristics—such as managerial myopia or agency frictions—that also influence how firms respond to productivity shocks. In the next empirical strategy section, we outline our empirical approach to isolate the variation in the cost of R&D that is driven solely by changes in R&D tax credits.

4 Empirical Strategy

This section describes our empirical specification for examining how firms of different sizes respond differently to productivity, and for identifying variation in R&D costs as the main channel underlying the size divergence.

4.1 Diverging Responses

We begin by examning how the cross-sectional relations between external financing (or investment) and productivity differ across firm size. We conduct Fama –MacBeth regression for firms from 1971 to 2019, where we first estimate cross-sectional regressions each year and then average the coefficients over the sample period. Because our initial focus is on cross-sectional patterns, we do not include firm fixed effects; instead, we allow firm-level heterogeneity to be captured through differences in firm size. This specification allows us to interpret the coefficients as reflecting how the correlation between external financing and productivity varies across firm size, while preserving time-invariant firm characteristics in the cross-section. The control variables in the Fama–MacBeth regressions include the lagged firm characteristics used in Frank and Goyal (2009). In addition, we include lagged cash holdings. Our theoretical framework highlights the importance of initial cash holdings, and our empirical strategy requires controlling for cross-sectional differences in firms' initial cash positions.

To examine how firms of different sizes respond differently to productivity, and to control for time-invariant factors that may affect external financing, we next turn to a panel-data analysis. In this specification, we include interactions between productivity and firm size.

$$y_{i,t} = \beta_0 + \beta_1 \text{Productivity}_{i,t} \times \text{Firm Size}_{i,t} + \beta_2 \text{Productivity}_{i,t} + \beta_3 \text{Firm Size}_{i,t} + x_{i,t-1} + \upsilon_i + \psi_t + \varepsilon_{i,t} \tag{6}$$

where the dependent variable $y_{i,t}$ is either firm external financing or investment. Firm Size$_{i,t}$ is firm size measured as the log of lagged total assets. As in our Fama–MacBeth regressions, we include firm characteristics measured at the beginning of the period. We also include firm fixed effects and year fixed effects. Standard errors are clustered at the firm level.

The coefficient of interest is β_1. When examining heterogeneity by firm size, a positive coefficient on β_1 indicates that larger firms increase external financing more in response to higher productivity, compared with smaller firms. This suggests that more productive large firms raise additional external capital.

4.2 Identify the Cost of R&D Channel

Our empirical strategy exploits the variation in firm-level R&D cost induced by the staggered introduction of state-level R&D tax credits from 1980 to 2007. These credits reduce the after-tax cost of research and development. The state-level policy variation is plausibly exogenous to individual firm financing decisions while directly affecting productivity through lower innovation costs.

With the state-level measure of R&D cost constructed by Wilson (2009), we then compute a firm-level measure of the user cost of R&D, defined as $\rho_{it} = \sum_s w_{ist}\rho_{st}$, where w_{ist} is the 10-year moving average of the location of firm's R&D activity using the location of its individual inventors, and ρ_{st} is state-level user cost of R&D.

The variation in our firm-level measure of the user cost of R&D comes from two sources: exogenous changes in state-level R&D tax policy and differences in inventor location. A key concern is that firms may endogenously choose where to locate their inventors in order to benefit from more favorable R&D tax credits. Such endogenous adjustments in inventor location may be correlated with other firm characteristics—such as managerial myopia or agency frictions—that also affect how firms respond to productivity shocks. To isolate the variation in R&D cost that is driven solely by state-level legislative changes, we employ a two-stage approach analogous to an instrumental variables strategy, using firm's headquarter state R&D tax credits as an instrument for the user cost of R&D. Because firms on average have a large share of their inventors located in the headquarter state, changes in the R&D tax credit of the headquarter state generate substantial variation in the user cost of R&D, leading to a strong first-stage relationship. The component of R&D cost explained by headquarter-state tax credits therefore captures exogenous variation that is unrelated to firm characteristics correlated with historical inventor locations.

As we need to include the interaction term $\text{Productivity}_{i,t} \times \text{R\&D Cost}_{i,t}$ to examine the divergent effect. Thus, we also run two first stage regressions also using the interaction term as dependent variable

In the first stage, we regress firm-level user cost of R&D on state-level tax credit.

$$\begin{aligned}\text{R\&D Cost}_{i,t} = \delta_0 + \delta_1 \text{State Tax Credit}_{s,t} + \delta_3 \text{Productivity}_{i,t} \times \text{State Tax Credit}_{s,t} \\ + \delta_4 \text{Firm Char.}_{i,t} + x_{i,t-1} + v_i + \psi_t + \varepsilon_{i,t}\end{aligned} \tag{7}$$

$$\begin{aligned}\text{Productivity} \times \text{R\&D Cost}_{i,t} = \gamma_0 + \gamma_1 \text{State Tax Credit}_{s,t} + \gamma_3 \text{Productivity}_{i,t} \times \text{State Tax Credit}_{s,t} \\ + \gamma_4 \text{Firm Char.}_{i,t} + x_{i,t-1} + v_i + \psi_t + \varepsilon_{i,t}\end{aligned} \tag{8}$$

where $\text{State Tax Credit}_{s,t}$ denotes the state-level R&D tax credit of firm i's headquarter state s, and $\text{Productivity}_{i,t} \times \text{State Tax Credit}_{s,t}$ is the interaction between firm i's productivity and the headquarter-state R&D tax credit. We include firm fixed effects to ensure that the variation we exploit is primarily within-firm over time. Based on the first-stage regressions, we then compute the predicted value of R&D cost, $\text{R\&D Cost}_{i,t}$, as well as the predicted value of the interaction term, $\text{Productivity}_{i,t} \times \text{R\&D Cost}_{i,t}$.

In the second-stage, we run the following regression

$$\begin{aligned}y_{i,t} = \beta_0 + \beta_1 \text{Predicted Productivity} \times \text{R\&D Cost}_{i,t} + \beta_2 \text{Predicted R\&D Cost}_{i,t} + \beta_3 \text{Productivity}_{i,t} \\ + \beta_4 \text{Firm Char.}_{i,t} + x_{i,t-1} + v_i + \psi_t + \varepsilon_{i,t}\end{aligned} \tag{9}$$

where $\text{Predicted Productivity} \times \text{R\&D Cost}_{i,t}$ and $\text{Predicted R\&D Cost}_{i,t}$ are obtained from the first-stage regressions. This second-stage specification ensures that the divergent responses we document are not driven by unobservable firm characteristics associated with the historical location of firm inventors.

The coefficient of interest is β_1. When analyzing differences across firms with varying R&D costs, a negative β_1 implies that high–R&D-cost firms reduce external financing more when productivity rises, compared with low–R&D-cost firms. This indicates that high–R&D-cost firms pay out more funds to external investors following a productivity increase.

4.3 Testing the Divergence Channel

Our theory demonstrates that the divergence in how large and small firms respond to productivity can be attributed to differences in their R&D costs. To more directly link the size-based pattern to the idea that large firms effectively face lower fixed costs of conducting R&D, we further test Proposition 2.4. The proposition implies that for firms facing higher expected fixed costs, the divergence in external finance between large and small firms weakens. In other words, as the cost of R&D rises, more productive large firms should be more likely to reduce external capital rather than raise it.

We implement a triple-interaction approach to test the theoretical predictions. Specifically, we estimate the following regression:

$$
\begin{aligned}
y_{i,t} = \beta_0 &+ \beta_1 \text{Productivity} \times \text{Firm Size} \times \text{R\&D Cost}_{i,t} + \beta_2 \text{Productivity} \times \text{Firm Size}_{i,t} \\
&+ \beta_3 \text{Productivity} \times \text{R\&D Cost}_{i,t} + \beta_4 \text{R\&D Cost} \times \text{Firm Size}_{i,t} \\
&+ \beta_5 \text{Firm Char.}_{i,t} + x_{i,t-1} + \upsilon_i + \psi_t + \varepsilon_{i,t}
\end{aligned} \tag{10}
$$

The coefficient of interest is β_1. Based on the theoretical prediction, we expect $\beta_1 < 0$, which implies that when a firm's R&D cost increase, the positive correlation between productivity and external financing for large firms should attenuate. In this test, we use the uninstrumented R&D Cost rather than instrumenting any interaction terms with R&D cost. Because this specification involves a triple interaction, the firm's choice of inventor location is unlikely to be correlated with the firm characteristics that determine how firms of different sizes respond to productivity shocks. For these reasons, we do not implement a two-stage instrumental variable approach for this particular test.

5 Evidence on Divergence in Firms' Responses

5.1 Data Description

Table 1 Panel C reports summary statistics by size quintile. Small firms (bottom quintile) have mean assets of $23.4 million and raise external financing equal to 20% of assets annually. Large firms (top quintile) have mean assets of \$7 billion and raise external financing equal to 2% of assets. Financing intensity declines smoothly across quintiles, from 20% to 2%. Productivity measures also vary systematically: small firms have mean productivity of 0.354, compared with 0.507 for large firms. The external financing composition differs across size groups: small firms rely heavily on equity issuance (15% of assets), whereas large firms rely almost entirely on debt (2.5% of assets). These systematic differences highlight the scale variation that our theoretical mechanism emphasizes.

The descriptive statistics in Table 1 Panel C provides initial support for our fixed cost mechanism. The smooth variation in financing patterns across size quintiles—with external financing rates of 20%, 10%, 7%, 4%, and 2% from smallest to largest firms—suggests continuous rather than discrete differences in financing needs. This pattern is inconsistent with traditional financing constraint models that predict sharp breaks between constrained and unconstrained firms (Fazzari et al., 1988; Kaplan and Zingales, 1997).

The substantial differences in average firm size across quintiles create precisely the scale economies our theory emphasizes. A \$10 million technology investment represents 43% of assets for a typical small firm but only 0.1% of assets for a typical large firm. This four-order-of-magnitude difference in relative costs provides the economic foundation for our hypothesis that identical productivity improvements generate opposite financing responses across the size distribution.

5.2 Baseline Results

Table 2 presents our core finding: small and large firms exhibit opposite financing responses to productivity improvements. We estimate the relationship between productivity and external financing separately for each size quintile, allowing the productivity coefficient to vary freely across firm sizes. The Fama-MacBeth regression results are reported for each group.

Panel A shows the effects on total external financing. Small firms exhibit a large negative response: a one-standard-deviation (0.634) increase in productivity reduces external financing by 3.3% $(0.634 * 0.052)$ of assets. The coefficient of -0.052 is highly significant with a t-statistic of -7.9, indicating this is not a statistical artifact. For a typical small firm with \$23 million in assets, this represents a \$0.76 million reduction in external capital raising.

Moving across size quintiles, the negative relationship steadily weakens. The second quintile reduces financing by 1% $(0.634 * 0.012)$ of assets (coefficient of -0.012, t-statistic of -8.1), while the third quintile external financing remains unchanged. For the largest firms, the relationship reverses. Large firms increase external financing following productivity improvements, with a coefficient of 0.004 that is statistically significant (t-statistic of 2.1), corresponding to increasing external financing by 0.3% ($0.634 * 0.004$) of assets.

The 3.6 percentage point difference between small and large firm responses represents 42% of mean financing levels (0.085), demonstrating substantial economic significance. This smooth transition across size quintiles aligns with our theoretical prediction of continuous variation driven by heterogeneous fixed costs, rather than discrete jumps predicted by representative firm models.

Panels B and C decompose external financing into debt and equity components. The divergent responses affect both financing sources, though with different magnitudes. Small firms reduce debt financing significantly, with a coefficient of -0.008 (t-statistic of -2.6). For large firms, the debt response reverses, with the top quintile showing a coefficient of 0.004 (t-statistic of 3.1).

The equity patterns are even stronger. Small firms dramatically reduce equity issuance following productivity improvements, with a coefficient of -0.040 (t-statistic of -6.0). A one-standard-deviation increase in productivity reduces equity financing by 2.5% ($0.634 * 0.04$) of assets. This 2.5% reduction represents the largest component of their overall financing response. The negative equity response persists across smaller firm quintiles, with even large firms showing a small negative coefficient, though statistically insignificant.

5.3 Investment Channel

Table 3 examines whether the financing differences translate into real investment disparities, as predicted by our theoretical framework. Panel A establishes the basic relationship between external financing and investment across all firms. For large firms, external financing predicts higher investment with a coefficient of 0.104 (t-statistic of 7.6), meaning each percentage point increase in external financing associates with a 0.109 percentage point increase in capital expenditure. This relationship holds consistently across size quintiles, with coefficients ranging from 0.065 for small firms to 0.104 for large firms.

Panel B provides more compelling evidence using fitted values of external financing driven by productivity shocks. This approach isolates variation in financing stemming from productivity improvements, providing a cleaner test of our mechanism. The fitted financing-investment relationship is stronger than the raw relationship.

Importantly, the fitted relationship varies significantly across firm size. Small firms show a coefficient of 0.080 (t-statistic of 9.1), while large firms exhibit a much stronger relationship with a coefficient of 0.123 (t-statistic of 9.9). This pattern aligns with our model's predictions: large firms that increase external financing following productivity improvements are precisely those adopting new technologies and investing heavily to amplify productivity gains. Small firms that reduce external financing correspondingly invest less, forgoing potentially profitable opportunities due to fixed cost constraints.

The economic magnitudes are substantial. For small firms, a 3.3% reduction in external financing translates into a 0.264% decline in investment rates. This represents a 4% decrease relative to the average investment rate of 0.068, indicating significant forgone investment opportunities.

5.4 Testing the Size Divergence

The previous sections have shown empirically a significant divergence in how small and large firms' external financing responds to productivity. The results are consistent with smaller firms taking on fewer investment opportunities following increases in productivity. Next, we formally test whether the heterogeneous responses of small and large firms to productivity shocks are statistically significant.

In the cross-sectional Fama–MacBeth results, we did not control for time-invariant firm-level factors when computing the raw differences between large and small firms. In our formal test, as outlined in equation 6 of the empirical strategy, we estimate a panel regression that includes an interaction between firm size and productivity, where firm size is measured using lagged log total assets. We also include firm and year fixed effects. The results are reported in Table 4.

The coefficient of interest is the interaction term between firm size and productivity. In Column (1), where the dependent variable is external finance, the coefficient on the interaction term is 0.01 (with a t-statistic of 9.2). This indicates that the relation between productivity and external financing is more positive for larger firms, consistent with the idea that more productive large firms raise additional external capital. The results remain similar when we examine net debt issuance and net equity issuance. In particular, the coefficient for net equity issuance in Column (3) is four times larger than the corresponding coefficient for net debt issuance in Column (2), which aligns with our cross-sectional findings that most of the heterogeneity is driven by changes in net equity issuance. Moreover, the positive coefficient in Column (4), where we examine firms' investment responses, is consistent with the underlying mechanism that larger firms are more likely to increase capital investment following positive productivity shocks.

6 Identifying the R&D Cost Channel

Empirically testing whether fixed costs of technology adoption create size-dependent investment thresholds poses an identification challenge. Unobservable firm characteristics shocks could affect the external financing of firms with high fixed costs of technology adoption and their productivity.

This section presents two sets of results that identify the R&D Cost Channel. First, we exploit firm-level variation in the fixed costs of technology adoption—measured by R&D costs and by variation induced through exogenous changes in state-level R&D tax credits. Second, we examine how size-dependent investment thresholds vary with changes in firm-level fixed costs of technology adoption, again measured by R&D cost. The results are consistent with the theoretical prediction that the costs of technology adoption generate size-dependent investment thresholds.

These analyses provide compelling evidence that productivity shocks causally generate the divergent financing responses documented earlier.

6.1 Variation in R&D Cost

Investment in R&D represents a fixed cost of technology upgrading, and our theoretical framework suggests that variation in this initial R&D investment creates size-dependent patterns in firms' responses. We argue that large firms face lower effective fixed costs of technology upgrade because they can spread these costs over a larger revenue base. Empirically, cross-firm variation in fixed costs can be proxied by differences in R&D cost. Among firms of similar size, a lower R&D cost indicates that the initial fixed cost required for technology upgrading is smaller relative to firms with higher R&D costs.

We use user cost of R&D to measure the fixed cost associated with technology adoption. We use Hall-Jorgensen formula for user cost of R&D, which is defined as $\rho_{st} = \frac{1-D_{st}}{1-\tau_{st}}[r_t + \delta]$, where D_{st} is tax credit, τ_{st} is corporate tax credit, and r_t is, and δ is the depreciation rate of R&D. Firm level user cost of R&D is defined as $\rho_{it} = \sum_s w_{ist}\rho_{st}$, where w_{ist} is the 10-year moving average of the location of firm's R&D activity using the location of its individual inventors, and ρ_{st} is state-level user cost of R&D.

The variation in our firm-level measure of the user cost of R&D is driven primarily by exogenous changes in state-level policies affecting the user cost of R&D. These policy shifts are plausibly exogenous to individual firms' financing decisions while directly influencing productivity by lowering the cost of innovation.

Unobserved firm characteristics could simultaneously drive both productivity and financing choices. Management quality, corporate culture, or investment opportunities may affect both variables, making it difficult to isolate the causal impact of R&D on how productivity on financing decisions. If better-managed firms both achieve higher productivity and make superior financing decisions, this could generate spurious correlations unrelated to our theoretical mechanism.

Because the primary variation in our measured R&D cost arises from changes in state-level policies, the resulting firm-level variation in R&D cost is unlikely to be driven by unobserved firm characteristics that could simultaneously affect productivity and financing choices. This helps ensure that the variation we exploit is not confounded by omitted firm-level factors.

The endogeneity main concern in our firm-level variation of R&D cost is the historical location of inventors, as firms could endogenously choose where inventors are based based on other unobservable firm characteristics. This concern is less prominent in the prior literature, because the location of inventors—while potentially chosen to benefit from lower R&D costs—is not correlated with other variables that affect their outcomes of interest. However, in our setting the endogenous location choice of inventors is more salient, as we aim to examine how firms' external financing decisions respond to productivity heterogeneity across firms with different R&D costs.

While our constructed firm-level R&D cost addresses most unobservable characteristics that directly affect the relationship between productivity and external financing, we further employ a two-stage instrumental variable approach to account for the possibility that unobserved firm characteristics may simultaneously influence both the location choices of inventors and the external financing decisions of high-productivity firms. Specifically, we use changes in the R&D tax credit of a firm's headquarter state as an instrument and compute the predicted change in the firm-level user cost of R&D.

6.2 Instrument Validity

Our instrumental variable is the R&D tax credit of a firm's headquarter state. Because the majority of a firm's innovative activity typically occurs in its headquarter state, changes in this state-level tax credit should have a significant impact on the firm's overall R&D cost, which we compute as the weighted average of R&D tax credits across the states in which its inventors are located.

The validity of our instrumental variable approach relies critically on the exclusion restriction. Conditional on firm and year fixed effects, the effect of productivity for high–R&D-cost firms should influence financing decisions only through its impact on R&D cost. The timing patterns are informative. We examine the timing of financing responses relative to credit introductions using event study methodology. Figure 2 gives event study plots. These show that financing responses happen immediately upon credit introduction and they persist for at least a few year. This is generally consistent with productivity-driven rather than temporary cash flow effects. The absence of major differences in the financing trends before credit introduction suggests that the parallel trends assumption is reasonable.

Another threat involves correlation between credit introductions and unobserved state-level factors that might independently affect corporate financing. States may introduce R&D tax credits during periods of economic growth or in response to competitive pressures that also influence firms' financing decisions. If credit timing correlates with state-level economic conditions or policy environments, our instrument could capture these confounding factors rather than isolating the productivity channel.

The political economy of credit adoption and conducting robustness tests with alternative specifications provide further support. The historical record suggests that R&D tax credits were typically introduced as part of broader economic development initiatives. They do not seem to have been responses to short-term economic conditions. Nor are they typically rapidly reversed when conditions change. The staggered timing across states and the persistence of effects over multiple years supports the view that the credits represent genuine policy innovations rather; and not responses to temporary economic circumstances.

6.3 First-Stage Results

Table 5 Panel A reports the first-stage regression results, estimated using the specification in equation 7. These results confirm the relevance of our instrument for identifying variation in R&D cost. Column (1) presents the first-stage regression instrumenting for the interaction between productivity and R&D cost, while Column (2) presents the first-stage regression instrumenting for R&D cost alone. The coefficient on the interaction between productivity and tax credits is -0.173 with a t-statistic of -12.7, and the coefficient on the tax credit variable is -0.063 with a t-statistic of -15.5. Both coefficients indicate that higher headquarter-state tax credit rates significantly reduce the user cost of R&D.

The first-stage F-statistic of 121.812 substantially exceeds conventional thresholds for weak instruments, confirming instrument strength. The Anderson-Rubin test yields a p-value of 0.000, providing additional evidence of instrument validity. These statistical measures demonstrate that R&D tax credits provide strong variation for identifying the productivity-financing relationship. The instrument satisfies standard requirements for instrumental variable analysis (Andrews et al., 2019; Keane and Neal, 2023).

6.4 Second-Stage Results and Economic Interpretation

Table 5 Panel B presents the second-stage results examining how instrumented R&D cost affects firms' financing decisions when productivity increases. The estimates follow the specification in equation 9. Results for external finance, net debt issuance, and net equity issuance are reported separately. The main finding is a large negative coefficient of -1.018 (with a t-statistic of -2.6) on the interaction between fitted productivity and R&D cost. This indicates that the reduction in external financing following productivity improvements is concentrated among firms facing higher R&D implementation costs. These patterns align closely with the predictions of our theoretical framework.

The R&D cost channel we document is highly significant. A one–standard deviation increase in R&D cost (0.022) leads to a 1% ($-1.018 * 0.022 * 0.451$) decrease in external financing as a share of assets, for a median productivity firm (0.451) when productivity increases. Given that the divergence results in Table 2 show that the difference in external financing between the top and bottom firm-size quintiles is 3.6% of total assets, a one–standard deviation change in R&D cost can explain 28% of this difference across firm sizes. This suggests that a 3.5–standard-deviation increase in R&D cost could fully account for the size divergence between large and small firms. The results are even stronger for higher-productivity firms (75th percentile, 0.652), where a one–standard-deviation increase in R&D cost can explain approximately 45% ($-1.018 \times 0.022 \times 0.652$) of the difference across firm sizes. In this case, only a 2.2–standard-deviation increase in R&D cost would be sufficient to explain the entire size divergence.

The decomposition into debt and equity responses reveals that both financing sources contribute to the overall pattern. Reductions in both net debt issuance and net equity issuance following productivity improvements are concentrated among firms facing higher R&D implementation costs. These patterns align closely with the predictions of our theoretical framework.

6.5 Placebo Tests

A critical threat to our identification strategy is that R&D tax credit introductions might coincide with unobserved economic or political factors that independently affect corporate financing decisions. If states introduce tax credits during periods of economic expansion or policy reform that also influence firm behavior, our instrument could capture these confounding factors rather than isolating the R&D cost channel. We address this concern through placebo tests that randomize the timing of tax credit introductions while preserving the overall structure of our analysis.

Our placebo tests apply the instrumental variables framework using randomly reassigned R&D tax credit timings as pseudo-instruments to validate the main identification strategy. By construction, these tests yield insignificant results, confirming that the primary findings are not driven by spurious correlations. In Table 6, Panel A reports the first-stage results using the randomized introduction of tax credits. As shown in Column (2), changes in the pseudo headquarter-state R&D tax credit do not affect firms' R&D cost, consistent with the empirical design of the placebo timing.

We then estimate the second-stage regressions using the fitted values from the first stage (Panel A), with results reported in Table 6 Panel B. These regressions examine the impact of instrumented R&D cost on corporate financing outcomes, including external finance, net debt issuance, and net equity issuance. The key regressor is the interaction between fitted productivity and the pseudo R&D cost. The coefficients on the interaction term are negative but statistically insignificant. This analysis demonstrates that placebo shocks do not affect financing decisions, in contrast to the significant effects observed when using actual tax-credit–driven variation in R&D cost.

Collectively, the insignificance in both stages strengthens the validity of the instrument. The IV approach helps isolate the true causal effect of variation in firm R&D cost on the relationship between productivity and financing.

6.6 Robustness to Zero R&D Firms

The mechanism of the R&D tax credit IV test is about the cost saving due to those credits. If a firm does no R&D then it gets no such credit. In this section we examine such firms. The results are in Table 7.

Panel A reports the first-stage regression results, estimated using the specification in equation 7. These results confirm the relevance of our instrument for identifying variation in R&D cost even among firms with zero current-period R&D investment. Importantly, firms that report zero R&D

in the current period may still have historical inventor locations and therefore remain eligible for state-level R&D tax credits. Thus, having zero current R&D investment does not imply that the firm's R&D cost is trivial. Consistent with the full-sample results, we find that an increase in the headquarter-state R&D tax credit is associated with a reduction in the user cost of R&D.

Panel B presents second-stage IV estimates for the subsample of 10,135 firm-year observations with no reported R&D spending. The fitted productivity-R&D cost interaction coefficient is -0.209 but statistically insignificant (t-statistic of -0.3). These results contrast with the significant negative coefficients found in our main sample (Table 5). The evidence indicates that our mechanism operates primarily through R&D-intensive technology adoption processes.

These findings provide important information about the scope of our theory. As might be expected, the mechanism is most relevant for firms engaged in R&D activities. For these firms fixed technology adoption costs are likely to be substantial and scale-dependent. Firms with zero R&D expenditures may face different types of investment opportunities. Their costs may not have the same fixed cost structure central to our model.

This evidence supports our theory emphasizing R&D tax credits as instruments that specifically target productivity-enhancing investments with significant fixed cost components. The extent to which our mechanism applies to other firms will depend on the importance of similar scale-dependent investment opportunities for those firms.

6.7 Triple Interaction Testing the R&D Cost Channel

So far, we have exploited exogenous variation in firm-level R&D cost as a measure of the fixed cost of innovation, and we have shown that the divergence in the size distribution of the productivity–financing relationship is likely driven by differences in firms' ability to spread fixed costs—an advantage that larger firms possess. In this section, we provide additional tests to demonstrate that the observed divergence across firms is indeed driven by differences in the fixed costs of innovation.

Our theoretical framework demonstrates that the divergence in how large and small firms respond to productivity can be attributed to differences in their R&D costs. To more directly link the size-based pattern to the idea that large firms effectively face lower fixed costs of conducting R&D, we further test Proposition 2.4. The proposition implies that for firms facing higher expected fixed costs, the divergence in external finance between large and small firms weakens. In other words, as the cost of R&D rises, more productive large firms should be more likely to reduce external capital rather than raise it.

We implement a triple-interaction approach to test the theoretical predictions. Specifically, we examine whether the alleviated reduction in external financing observed for large firms following productivity improvements becomes less pronounced when R&D costs increase. In other words, when R&D costs rise, the relative increase in external financing for high-productivity large firms—compared with smaller firms—should be less significant.

In this test, we use R&D Cost rather than instrumenting any interaction terms with R&D cost. Because this specification involves a triple interaction, the firm's choice of inventor location is unlikely to be correlated with the firm characteristics that determine how firms of different sizes respond to productivity shocks. Moreover, the exogenous variation in state-level tax credits helps rule out unobservable firm characteristics that do not affect changes in inventor location. For these reasons, we do not implement a two-stage instrumental variable approach for this particular test.

Table 8 Panel A reports the triple-interaction results. In Column (1), we replicate the heterogeneity test from Table 4, restricting the sample to the period in which state-level R&D tax credits vary. The coefficient on the interaction between productivity and firm size is positive, consistent with our baseline finding that larger firms increase external financing more in response to productivity improvements. Column (2) adds the triple interaction among productivity, firm size, and R&D cost. The coefficient on this term is negative and statistically significant. This indicates that the additional external financing raised by larger firms in response to productivity shocks is smaller when these firms face higher R&D costs. This result supports the interpretation that the amplified financing response of large firms is indeed driven by their lower effective fixed costs of innovation.

Table 8 Panel B provides additional results examining how the relationship varies across firm-size groups for firms facing high versus low R&D costs. We sort firms by their R&D costs and analyze the relationship between external finance and productivity. Columns (1) and (2) report results for firms in the top quartile of R&D costs—firms that are most likely to face high fixed costs of technology adoption. For these firms, both small and large firms exhibit negative productivity–financing relationships, with coefficients of -0.091 and -0.008, respectively. This pattern aligns with our theoretical prediction that high fixed costs can make technology adoption unprofitable even for large firms.

Conversely, in Columns (3) and (4), for firms in the bottom quartile of R&D costs, the relationship becomes positive for large firms (coefficient of 0.004) while remaining negative and insignificant for small firms. This heterogeneity provides direct support for our fixed cost mechanism by showing that the productivity–financing relationship depends systematically on the costs of technology adoption.

6.8 General Tax Policy

Our previous results establish that the R&D tax credit serves as an incentive for firms' external financing behavior and helps explain the divergence between large and small firms. Next, we provide additional robustness tests to ensure that our results are not driven by general tax incentives unrelated to R&D.

To rule out the effect of non–R&D-related tax incentives, we exploit the empirical setting from Zwick and Mahon (2017), which examines how bonus depreciation—an accelerated schedule that allows firms to deduct the cost of investment purchases from taxable income more quickly—affects corporate investment. Their study uses cross-industry variation in bonus depreciation. If our results were driven by general tax incentives such as accelerated depreciation, we should observe differential external financing responses between large and small firms when bonus depreciation changes.

We conduct similar tests by replacing R&D costs with firm-level bonus depreciation. The corresponding results are reported in Table 9. Table 9 Panel A reports the triple-interaction results. The coefficient on the triple interaction term among productivity, firm size, and bonus depreciation is insignificant. This result supports the interpretation that the amplified financing response of large firms is not driven by bonus depreciation incentives.

Table 9 Panel B provides additional results examining how the relationship varies across firm-size groups for firms facing high versus low bonus depreciation. Consistent with the results from Panel A, we do not find that large and small firms react differently when they face different levels of bonus depreciation. This heterogeneity provides a robustness test showing that the productivity–financing relationship is not driven by general tax incentives.

7 Economic Magnitude

This section quantifies the economic significance of our findings. We translate our estimated coefficients into economic magnitudes. We analyze the mechanism's contribution to productivity dispersion, and consider some policy aspects.

7.1 Contribution to Productivity Dispersion

A major question in finance and macroeconomics is to understanding the forces driving increased productivity dispersion and the emergence of superstar firms (Hsieh and Klenow, 2009; Autor et al., 2020; De Loecker et al., 2020; Ayyagari et al., 2024). Here we consider the extent to which our mechanism contributes meaningfully to these aggregate trends. To do that we construct counterfactual scenarios that eliminate size-dependent financing responses to productivity improvements.

We compare actual productivity evolution with counterfactual paths where all firms exhibit uniform financing responses equal to the asset-weighted sample average. We translate different financing responses into investment differences using our estimated elasticities from Table 3. Then we calculate how these investment differences compound into productivity dispersion over time. The analysis relies on standard assumptions from the endogenous growth literature linking investment to future productivity growth. Complete details of the methodology, parameter choices, and robustness analysis are provided in Appendix Appendix D.

The results provide striking evidence that our mechanism contributes substantially to rising productivity dispersion. Figure 3 shows the evolution of the 90th-10th percentile productivity ratio from 1970 to 2019 under actual and counterfactual financing responses. Under actual responses, productivity dispersion increases by 45% over the sample period. Eliminating differential financing responses reduces this increase to 37%, implying that our mechanism accounts for 18% of the observed dispersion growth.

In Figure 3 the solid black line shows actual productivity dispersion, measured by the 90th-10th percentile ratio, increasing from 2.84 in 1970 to 4.12 in 2019—a 45% rise over five decades. The dashed blue line is a counterfactual path in which all firms are assumed to have uniform financing responses to productivity shocks. That eliminates the fixed cost mechanism of small firms reducing external financing while large firms increase it. Under this counterfactual, dispersion rises more modestly to 3.89, representing only a 37% increase. The gray shaded area between the curves shows the impact of our mechanism. It accounts for 8 of the 45 percentage points of dispersion growth (18% of the total increase). Due to compounding the mechanism's importance increases over time. It contributed essentially nothing to dispersion in the 1970s. It accounts for over 25% of dispersion growth in the post-2000 period. This time pattern matches the increasing importance of technologies requiring substantial fixed investments. These include things like information systems and digital platforms. These favor firms with sufficient scale to justify adoption costs.

The size-specific effects explain how the mechanism operates. Under actual financing responses, large firms achieve 1.31% average annual productivity growth compared to 0.84% for small firms over the full sample period. Eliminating the response gap compresses this gap from 0.47 to 0.31 percentage points. That is a 34% reduction. The mechanism amplifies large firm productivity advantages while constraining small firm growth. As a result it generates feedback loops that drive increasing concentration.

Sensitivity analysis shows these findings are robust across reasonable parameter assumptions. Conservative estimates suggest the mechanism accounts for at least 11% of dispersion growth. More aggressive assumptions suggest contributions up to 25%. Manufacturing firms show larger effects (22%). This makes sense due to their higher fixed costs of technology adoption. Excluding the technology sector produces smaller but still substantial effects (16%).

These quantitative results demonstrate that corporate financing decisions interact with real investment choices in ways that meaningfully affect macroeconomic outcomes. The mechanism provides a microfoundation for aggregate productivity trends that complements existing explanations based on technological change, market power, or globalization. Unlike these alternatives, our channel operates through the internal capital allocation decisions of firms rather than external market forces.

The findings also help explain why standard Q-theory models sometimes struggle in empirical tests (Bond and Van Reenen, 2007). Averaging across firms with systematically different responses to productivity shocks obscures underlying economic relationships. Our results suggest that firm heterogeneity in scale constraints represents a fundamental feature of modern economies rather than a statistical nuisance to be controlled away. This evidence is generally consistent with Andrei et al. (2019). They find that Q-theory works much better in recent decades. That is precisely when our technology/fixed cost mechansim has become increasingly important.

7.2 Policy Implications and Welfare Considerations

Our findings challenge conventional approaches to small business policy that focus primarily on alleviating financing constraints. The evidence suggests that many small firm challenges stem from scale-dependent investment opportunities rather than financing access per se. When the fundamental constraint involves fixed costs of technology adoption, policies that simply increase credit availability may prove ineffective.

Policy design involves important tradeoffs. Completely eliminating the size disadvantage may not be economically efficient. The large firms' ability to spread fixed costs over substantial scale generates legitimate efficiency gains. Those gains contribute to aggregate productivity growth. If policy makers wish to support for small firm competitiveness, this would need to be balanced against the preservation of scale economies that benefit overall economic performance. As mentioned previously financial subsidies to the financing of small firms may even be ineffective as the money is simply passed through to the owners.

Several limitations and caveats affect the interpretation of our magnitude calculations. The productivity-investment relationship involves substantial uncertainty. Our estimates rely on assumptions about the persistence of investment differences over time. The specific technologies and fixed cost structures driving our results may vary significantly across industries and time periods, affecting the generalizability of our findings. Investigating the pervasiveness of diverging paths across countries in future research could help speak to this issue.

8 Conclusion

This paper shows that small and large firms exhibit opposite financing responses to productivity improvements. Using comprehensive U.S. data from 1971 to 2019, we show that small firms reduce external financing by 3.3% of assets following productivity increases, while large firms increase it by 0.3%. Causal identification using state R&D tax credits confirms these patterns with even larger magnitudes in the IV estimation.

We provide a model based on fixed costs of technology adoption that explains this divergence. Small firms cannot justify fixed costs despite productivity gains. Large firms can spread costs over sufficient scale. So the small firms take advantage of good times to reward investors and large firms take advantage of good times to invest more heavily. The mechanism operates through real investment decisions and creates feedback loops that amplify initial productivity differences.

Our findings help resolve issues in Q-theory tests (Bond and Van Reenen, 2007; Andrei et al., 2019) and provide a microfoundation for rising productivity dispersion (De Loecker et al., 2020; Kehrig and Vincent, 2021; Ayyagari et al., 2024). It can explain approximately 18% of increased dispersion from 1970 to 2019. The results call into question conventional small business subsidies that are based on an assumption that the small firms are coping with financing constraints. If scale-dependent investment opportunities are the binding constraint for the small firms, the subsidy funds may simply be passed along to the firm owners. As economies shift toward high-fixed-cost technologies, understanding these scale effects becomes increasingly important for both theory and policy.

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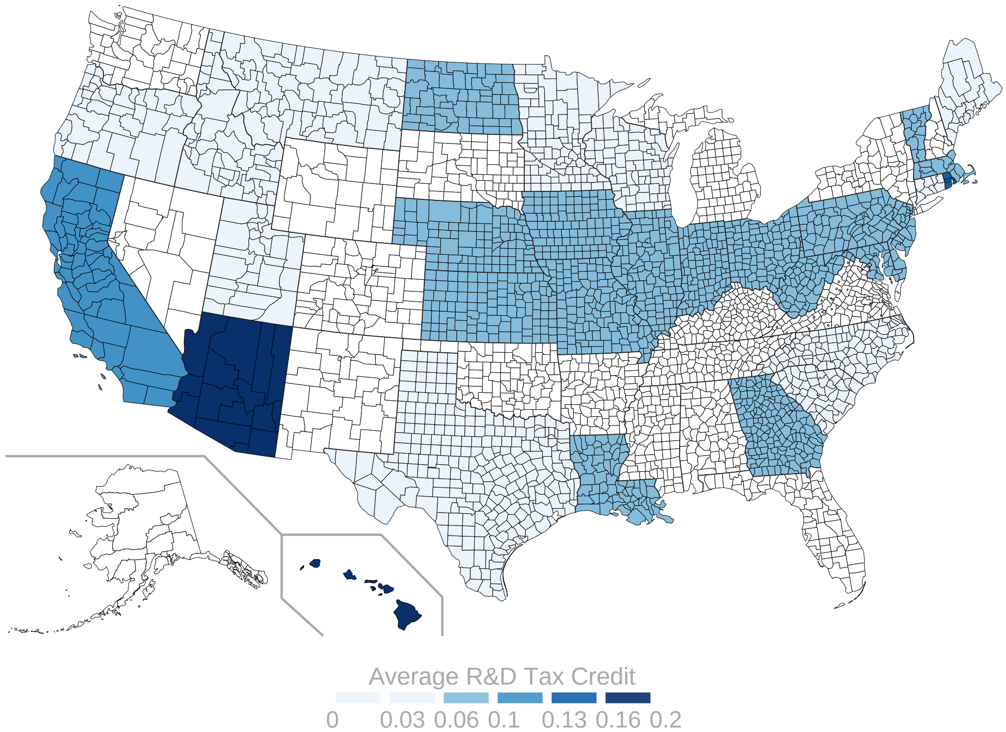
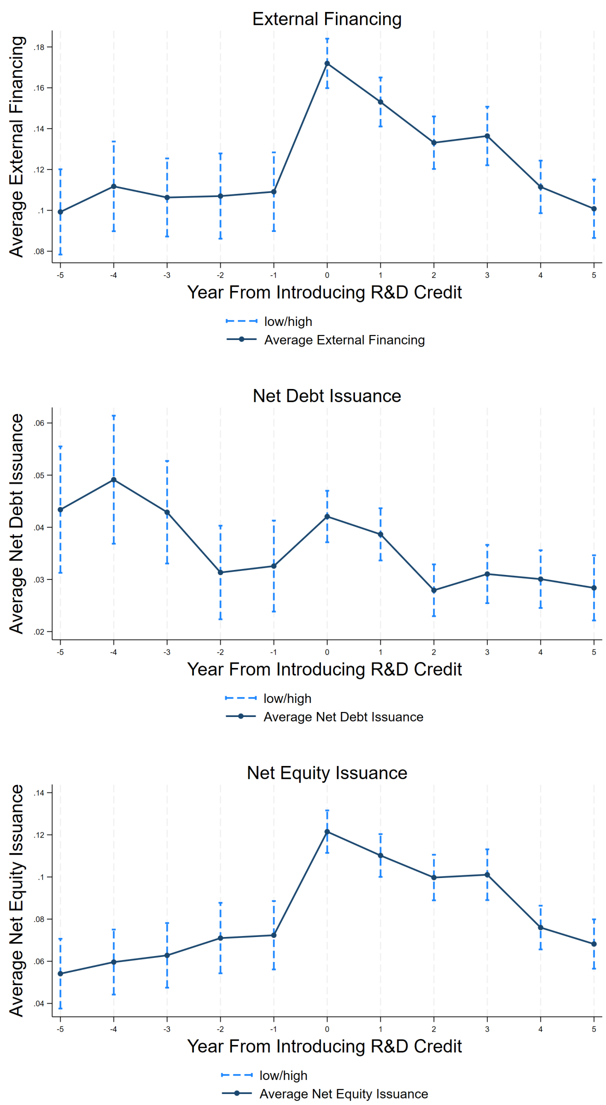
Tables and Figures

Figure 1: State-Level R&D Tax Credit Adoption



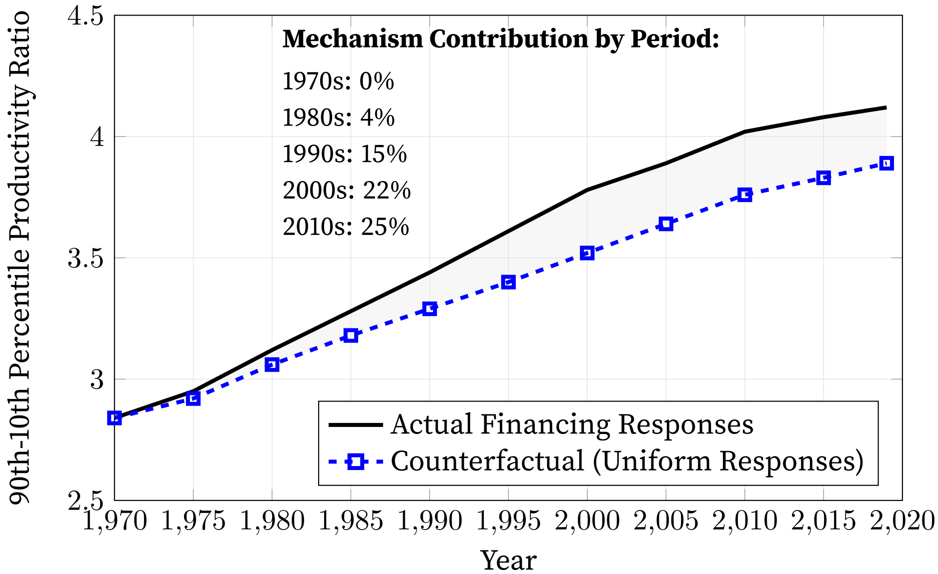
This figure displays the geographic distribution of state-level R&D tax credit rates. Darker shading indicates higher average tax credit rates over the sample period. Twenty-nine states introduced or expanded R&D tax credits between 1981 and 2006, providing variation for identification. The staggered timing of adoptions across states generates plausibly exogenous variation in productivity incentives.

Figure 2: Dynamic Response to R&D Tax Credit Introduction



This figure presents event study plots around the introduction of state R&D tax credits. The x-axis shows years relative to credit introduction (year 0). The y-axis shows average financing flows scaled by assets. Small firms reduce external financing following credit introduction while large firms increase it. The absence of pre-trends supports the identification assumption, while the persistent post-treatment effects confirm the causal interpretation.

Figure 3: Evolution of Productivity Dispersion: Actual vs. Counterfactual



This figure shows the evolution of productivity dispersion measured by the 90th-10th percentile ratio of firm-level total factor productivity from 1971 to 2019. The solid line shows actual dispersion under observed financing responses to productivity improvements. The dashed line shows counterfactual dispersion assuming all firms exhibit uniform financing responses equal to the asset-weighted sample average. The shaded area represents the contribution of size-dependent financing responses to rising productivity dispersion. Productivity is measured using residuals from production function regressions estimated separately by industry and decade. The mechanism's contribution grows from essentially zero in the 1970s to over 25% in the post-2000 period.

Table 1: Summary Statistics

Panel A: Firm Characteristics								
Variable	Mean	Std Dev	P25	Median	P75	Min	Max	N
Productivity	0.471	0.634	0.225	0.518	0.772	-5.855	8.550	141767
External Finance	0.085	0.288	-0.024	0.003	0.077	-0.331	3.481	141767
Net Debt Issue	0.032	0.142	-0.019	0.000	0.043	-0.378	1.296	141767
Net Equity Issue	0.050	0.223	-0.001	0.000	0.010	-0.364	3.302	141767
Lagged Assets ($M)	1629.757	5406.707	49.430	186.597	826.023	1.463	85120.125	141767
Lagged LnAssets	5.377	1.995	3.921	5.234	6.718	0.902	11.352	141767
Panel B: Firm Characteristics for Firms with an R&D Cost Measure								
Variable	Mean	Std Dev	P25	Median	P75	Min	Max	N
Productivity	0.359	0.633	0.127	0.451	0.652	-3.870	8.550	39942
R&D Cost	0.146	0.022	0.133	0.144	0.166	0.001	0.183	39942
External Finance	0.094	0.323	-0.024	0.005	0.070	-0.331	3.481	39942
Net Debt Issue	0.027	0.136	-0.018	0.000	0.032	-0.378	1.296	39942
Net Equity Issue	0.063	0.267	-0.001	0.001	0.015	-0.364	3.302	39942
Lagged Assets ($M)	1805.573	4721.074	57.384	211.853	976.817	1.463	38649.277	39942
Lagged LnAssets	5.535	2.018	4.067	5.361	6.885	0.902	10.562	39942

Panel C: Firm Characteristics by Firm Size					
	(1)	(2)	(3)	(4)	(5)
Size Quintiles	Small	2	3	4	Large
Productivity	0.354	0.455	0.512	0.528	0.507
External Finance	0.199	0.098	0.065	0.044	0.020
Net Debt Issue	0.037	0.032	0.034	0.034	0.025
Net Equity Issue	0.152	0.063	0.028	0.009	-0.005
Lagged Assets ($M)	23.385	91.427	259.086	765.613	7014.258
Lagged LnAssets	2.873	4.255	5.253	6.319	8.188
Observations	28372	28356	28350	28356	28333

This table reports summary statistics. Panel A reports summary statistics for the main sample variables from 1971 to 2019. Panel B reports summary statistics for the R&D cost sample covering firms from 1980 to 2007. Panel C reports mean values for the main variables from 1971 to 2019, sorted by firm-size quintiles based on lagged total assets. External finance is defined as the sum of net debt and equity issuance, scaled by lagged assets. Productivity is estimated from industry-decade production functions. All variables are winsorized at the 1st and 99th percentiles.

Table 2: Productivity and External Financing by Firm Size

	Size Quintile				
	(1) Small	(2) 2	(3) 3	(4) 4	(5) Large
Panel A: Total External Financing					
Productivity	-0.052***	-0.012**	-0.002	0.004	0.004**
	(-6.6)	(-2.4)	(-0.4)	(1.3)	(2.1)
Observations	28372	28356	28350	28356	28333
Adjusted R^2	0.328	0.160	0.094	0.063	0.053
Panel B: Net Debt Issuance					
Productivity	-0.008**	-0.001	0.003	0.006**	0.004***
	(-2.6)	(-0.5)	(1.1)	(2.6)	(3.1)
Observations	28372	28356	28350	28356	28333
Adjusted R^2	0.041	0.031	0.034	0.030	0.035
Panel C: Net Equity Issuance					
Productivity	-0.040***	-0.012***	-0.006**	-0.002	-0.000
	(-6.0)	(-3.3)	(-2.4)	(-1.3)	(-0.5)
Observations	28372	28356	28350	28356	28333
Adjusted R^2	0.329	0.185	0.116	0.094	0.117

This table reports the estimated effects of productivity on financing from 1971 to 2019. Firms are sorted into quintiles based on lagged total assets. Fama-MacBeth regression coefficients are reported, with controls following Frank and Goyal (2009). T-statistics are shown in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: External Financing and Investment

	Size Quintile				
	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Investment	Small	2	3	4	Large
Panel A: External Financing					
External Finance	0.065***	0.070***	0.099***	0.100***	0.104***
	(6.1)	(6.1)	(6.9)	(7.0)	(7.6)
Observations	28372	28356	28350	28356	28333
Adjusted R^2	0.245	0.330	0.400	0.432	0.409
Panel B: Fitted External Financing					
Fitted External Finance	0.080***	0.095***	0.119***	0.121***	0.123***
	(9.1)	(8.2)	(10.6)	(11.6)	(9.9)
Observations	28372	28356	28350	28356	28333
Adjusted R^2	0.232	0.316	0.376	0.409	0.396

This table reports regressions of investment on external financing from 1971 to 2019. Investment is capital expenditure scaled by lagged assets. Panel B uses fitted financing values from productivity regressions. Firms are sorted into quintiles based on lagged total assets. Fama-MacBeth regression coefficients are reported. T-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Firm Size Heterogeneity Effects

	(1) External Finance	(2) Net Debt Issuance	(3) Net Equity Issuance	(4) Investment
Productivity×Lagged LnAsset	0.010***	0.002***	0.008***	0.001**
	(9.2)	(3.8)	(8.9)	(2.3)
Productivity	-0.082***	-0.015***	-0.065***	-0.005***
	(-9.3)	(-4.0)	(-8.9)	(-2.7)
Lagged LnAsset	-0.083***	-0.019***	-0.057***	-0.005***
	(-40.0)	(-20.5)	(-36.0)	(-10.1)
Firm, Year FE	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes
Observations	141767	141767	141767	141767
Adjusted R^2	0.374	0.110	0.406	0.538

This table reports the heterogeneity effects of productivity on external financing from 1971 to 2019. Panel regression coefficients are presented, with controls following Frank and Goyal (2009), along with lagged cash holdings. Firm and year fixed effects are included, and standard errors are clustered at the firm level. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Identifying R&D Channel using Instrumental Variable

Panel A: First Stage

Dependent Variable:	(1) Productivity×R&D Cost	(2) R&D Cost
Productivity×Tax Credit	-0.173***	
	(-12.7)	
Productivity	0.146***	
	(102.2)	
Tax Credit		-0.063***
		(-15.5)
Firm, Year FE	Yes	Yes
Control Variables	Yes	Yes
Observations	39942	39942
Adjusted R^2	0.987	0.929
Wald F-statistic	121.812	
Anderson-Rubin Wald test p-value	0.000	

Panel B: Second-Stage IV Estimates

Dependent Variable:	(1) External Finance	(2) Net Debt Issue	(3) Net Equity Issue
Fitted Productivity×R&D Cost	-1.018***	-0.301*	-0.512
	(-2.6)	(-1.7)	(-1.5)
Productivity	0.134**	0.040	0.066
	(2.5)	(1.6)	(1.4)
Fitted R&D Cost	0.977	0.620	0.219
	(0.9)	(1.2)	(0.3)
Firm, Year FE	Yes	Yes	Yes
Control Vars	Yes	Yes	Yes
Observations	39942	39942	39942
Adjusted R^2	0.202	0.015	0.195

This table reports the IV regressions using state-level R&D tax credits from 1980 to 2007. Panel A presents the first-stage regression results, where the instruments are the state–year-specific R&D tax credit rate of a firm's headquarter state and its interaction with firm productivity. The instrumented variables are the firm-level R&D cost and the interaction between R&D cost and productivity. Panel B reports the second-stage regression results, in which inancial flows are regressed on the fitted interaction between productivity and R&D cost. All regressions include year and firm fixed effects, as well as the control variables from Frank and Goyal (2009). Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. *** indicates significance at the 1% level.

Table 6: Causal Identification Placebo Test

Panel A: First Stage		
	(1)	(2)
Dependent Variable:	Productivity×R&D Cost	R&D Cost
Productivity×Pseudo Tax Credit	-0.117***	
	(-9.3)	
Productivity	0.142***	
	(116.5)	
Pseudo Tax Credit		-0.001
		(-0.1)
Firm, Year FE	Yes	Yes
Control Variables	Yes	Yes
Observations	39942	39942
Adjusted R^2	0.986	0.925

Panel B: Second-Stage IV Estimates			
	(1)	(2)	(3)
Dependent Variable:	External Finance	Net Debt Issue	Net Equity Issue
Pseudo Fitted Productivity×R&D Cost	-5.078	-3.421	-0.104
	(-0.1)	(-0.1)	(-0.0)
Productivity	0.651	0.442	0.007
	(0.1)	(0.1)	(0.0)
Pseudo R&D Cost	170.462	110.761	11.829
	(0.1)	(0.1)	(0.1)
Firm, Year FE	Yes	Yes	Yes
Control Vars	Yes	Yes	Yes
Observations	39942	39942	39942
Adjusted R^2	-13.677	-25.773	0.096

This table reports the IV regressions using state-level R&D tax credits from 1980 to 2007. Panel A presents the first-stage regression results, where the instruments are our pseudo instrumental variable, which is the interaction between productivity and state-year-specific pseudo tax credits in the state of the firm's headquarters. Panel B reports the second-stage regression results, in which financial flows are regressed on the fitted interaction between productivity and R&D cost. All regressions include year and firm fixed effects, as well as the control variables from Frank and Goyal (2009). Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. *** indicates significance at the 1% level.

Table 7: Zero R&D Firms

Panel A: First Stage		
Dependent Variable:	(1) Productivity×R&D Cost	(2) R&D Cost
Productivity×Tax Credit	-0.164***	
	(-8.8)	
Productivity	0.150***	
	(108.5)	
Tax Credit		-0.043***
		(-4.5)
Firm, Year FE	Yes	Yes
Control Variables	Yes	Yes
Observations	10135	10135
Adjusted R^2	0.987	0.877
Wald F-statistic	65.505	
Anderson-Rubin Wald test p-value	0.000	

Panel B: Second-Stage IV Estimates			
Dependent Variable:	(1) External Finance	(2) Net Debt Issue	(3) Net Equity Issue
Fitted Productivity×R&D Cost	-0.209	-0.744	0.530
	(-0.3)	(-1.6)	(1.5)
Productivity	0.022	0.103	-0.081
	(0.2)	(1.5)	(-1.5)
Fitted R&D Cost	3.040	1.812	1.134
	(1.0)	(1.0)	(0.6)
Firm, Year FE	Yes	Yes	Yes
Control Vars	Yes	Yes	Yes
Observations	10135	10135	10135
Adjusted R^2	0.071	0.008	0.096

This table reports the IV regressions using state-level R&D tax credits from 1980 to 2007, using a sample of firms with zero R&D expenditures. Panel A presents the first-stage regression results, where the instruments are the state–year-specific R&D tax credit rate of a firm's headquarter state and its interaction with firm productivity. The instrumented variables are the firm-level R&D cost and the interaction between R&D cost and productivity. Panel B reports the second-stage regression results, in which financial flows are regressed on the fitted interaction between productivity and R&D cost. All regressions include year and firm fixed effects, as well as the control variables from Frank and Goyal (2009). Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. *** indicates significance at the 1% level.

Table 8: Identifying R&D Channel using Triple Interaction

Panel A: Triple Interaction

	(1)	(2)
Dependent Variable:	External Finance	
Productivity×Lagged LnAssets ×R&D Cost		-0.056*
		(-1.7)
Productivity×Lagged LnAssets	0.012***	0.020***
	(5.6)	(3.9)
Productivity	-0.089***	-0.083***
	(-5.2)	(-4.7)
R&D Cost		-0.054**
		(-2.5)
R&D Cost×Lagged LnAssets		0.133***
		(3.4)
Productivity×R&D Cost		0.052*
		(1.7)
Firm, Year FE	Yes	Yes
Control Variables	Yes	Yes
Observations	39942	39942
Adjusted R^2	0.423	0.423

Panel B: Sort Firms by R&D Cost

	(1)	(2)	(3)	(4)
	High R&D Cost		Low R&D Cost	
	Small Firms	Large Firms	Small Firms	Large Firms
Productivity	-0.091**	-0.008*	-0.056	0.004
	(-2.3)	(-1.8)	(-1.6)	(1.6)
Firm, Year FE	Yes	Yes	Yes	Yes
Control Vars	Yes	Yes	Yes	Yes
Observations	2284	2321	2229	2330
Adjusted R^2	0.399	0.057	0.545	0.176

This table reports the triple-difference results for firms from 1980 to 2007. Panel A presents the baseline triple-difference estimates from estimating equation 10. The dependent variable is external finance, and the independent variables include the interaction among productivity, lagged log assets, and R&D cost, as well as the corresponding two-way interactions. Panel B reports regression results obtained by regressing firm external finance on firm productivity, separately for firms sorted by R&D cost and firm size. High (Low) R&D Cost firms are those in the top (bottom) quartile of the R&D cost distribution. Large (Small) firms are those in the top (bottom) quartile of lagged log assets. All regressions include year and firm fixed effects, as well as the control variables from Frank and Goyal (2009). Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. *** indicates significance at the 1% level.

Table 9: General Tax Policy

Panel A: Triple Interaction		
	(1)	(2)
Dependent Variable:	External Finance	
Productivity×Lagged LnAssets ×Bonus Depreciation		0.032
		(0.5)
Productivity×Lagged LnAssets	0.019***	-0.010
	(9.0)	(-0.2)
Productivity	-0.129***	0.101
	(-8.9)	(0.3)
Bonus Depreciation		-1.891***
		(-2.6)
Bonus Depreciation×Lagged LnAssets		-0.041
		(-0.8)
Productivity×Bonus Depreciation		-0.258
		(-0.6)
Firm, Year FE	Yes	Yes
Control Variables	Yes	Yes
Observations	75299	75299
Adjusted R^2	0.369	0.369

Panel B: Sort Firms by R&D Cost				
	(1)	(2)	(3)	(4)
	High R&D Cost		Low R&D Cost	
	Small Firms	Large Firms	Small Firms	Large Firms
Productivity	-0.121***	-0.000	-0.120***	-0.002
	(-3.2)	(-0.0)	(-3.1)	(-0.6)
Firm, Year FE	Yes	Yes	Yes	Yes
Control Vars	Yes	Yes	Yes	Yes
Observations	4613	3700	3231	6802
Adjusted R^2	0.466	0.208	0.342	0.185

This table reports the triple-difference results for firms from 1980 to 2007. Panel A presents the baseline triple-difference estimates, analogous to Panel A of Table 8. The dependent variable is external finance, and the independent variables include the interaction among productivity, lagged log assets, and bonus depreciation, as well as the corresponding two-way interactions. Bonus depreciation is measured using industry-level exposure to accelerated depreciation bonuses following Zwick and Mahon (2017). Panel B reports regression results obtained by regressing firm external finance on firm productivity, separately for firms sorted by bonus depreciation and firm size. High (Low) bonus depreciation firms are those in the top (bottom) quartile of the bonus depreciation distribution. Large (Small) firms are those in the top (bottom) quartile of lagged log assets. All regressions include year and firm fixed effects, as well as the control variables from Frank and Goyal (2009). Standard errors are clustered at the firm level, and t-statistics are reported in parentheses. *** indicates significance at the 1% level.

Appendix A Theoretical Derivations

Proof. For proposition 2.1. For larger firms with lower fixed costs of upgrade, the adopt region dominates. Thus, increases in productivity lead to higher expected external financing. For smaller firms with higher fixed costs of upgrade, the non-adopt region dominates, and $[1 - F(\bar{\phi}(a_i))]$ is close to one. In this case, when productivity increases, firms return more cash to investors. $\square$

Proof. For proposition 2.2. $\Delta\pi_i = \kappa a_i^{\sigma-1}(h^{\sigma-1} - 1)$ is continuous and strictly increasing in a_i. The cumulative distribution function $F(\cdot)$ is continuous by assumption. So the expected external financing function $E[e_i|a_i]$ is continuous in a_i. The derivative $\frac{\partial E[e_i|a_i]}{\partial a_i}$ therefore varies smoothly without discrete jumps. $\square$

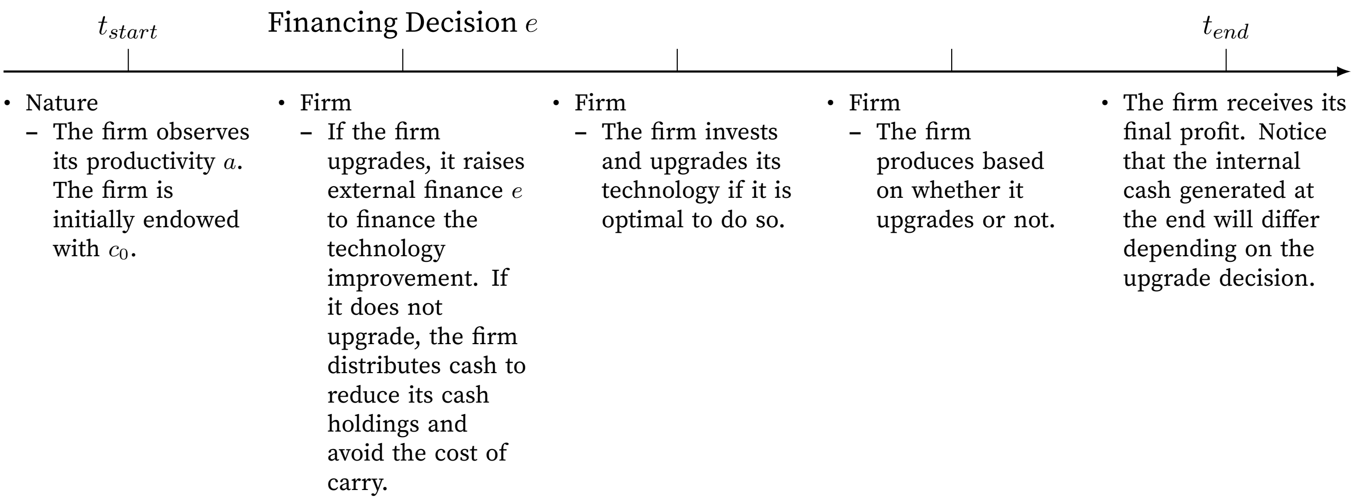
Proof. For proposition 2.3. From the model structure, firms that increase external financing following productivity improvements ($\frac{\partial E[e_i|a_i]}{\partial a_i} > 0$) are precisely those that adopt the new technology and invest ϕ_i in productivity enhancement. Firms that reduce external financing ($\frac{\partial E[e_i|a_i]}{\partial a_i} < 0$) are non-adopters that invest zero in the technology. Therefore, investment in productivity-enhancing activities is strictly higher for the former group. $\square$

Proof. For proposition 2.4. In a high fixed-cost setting, productivity improvements are unlikely to justify adoption for either small or large firms. For smaller firms, the non-adoption region dominates because fixed costs frequently exceed the gain from upgrading. For larger firms, although they face lower expected fixed costs, high fixed-cost realizations still make adoption unlikely. As a result, both small and large firms behave similarly in the non-adoption region, and the difference in external finance between them weakens. In a low fixed-cost setting, productivity improvements are more likely to justify adoption for both small and large firms. For smaller firms, the adopt region becomes more prominent as productivity increases. For larger firms, with even lower expected fixed costs, the adopt region dominates even more strongly. In this case, because large firms face a higher likelihood of adopting and raising external finance, while smaller firms do so less frequently, the divergence in external financing responses becomes stronger. $\square$

Proof. For proposition 2.5. The adoption threshold is $\bar{\phi}(a_i) = \frac{\Delta\pi_i + rc_0}{1+r}$ for firms requiring external financing. A reduction in fixed costs $\Delta\phi$ increases the threshold by $\Delta\phi$. A reduction in the financing wedge Δr increases the threshold by $\frac{c_0}{(1+r)^2}\Delta r$. Since $\Delta\phi > \frac{c_0}{(1+r)^2}\Delta r$ for equivalent policy costs, fixed cost reductions generate larger threshold changes. That implies larger financing response changes. $\square$

External Finance Time Line To connect our theory to financing decisions, we make the following assumption: after the end of the production period, the firm seeks to maintain an optimal level of cash holdings. Therefore, firms that do not upgrade will pay out some of their internal cash to shareholders. In contrast, firms that have already exhausted their internal cash holdings will raise additional funds c_0 to restore their internal cash to the optimal level.

Figure A1: Order of Events Within Period t



Appendix B Sample Construction

Table A1 documents the sample construction process. We start with all Compustat/CRSP observations and apply standard filters used in corporate finance research to ensure data quality and comparability across firms.

Appendix C Production Function Estimation

We estimate productivity using production function residuals estimated separately by industry and decade, controlling for observed inputs and technological differences. We adapt standard production function methods to corporate accounting data by modeling sales as a function of three inputs that capture the opportunity cost of firm resources. A helpful review of production function estimation is De Loecker and Syverson (2021).

Table A1: Data Cleaning

Step	Observations
Start: COMPUSTAT/CRSP Fundamentals Annual Merged 1950 to 2019	326,248
Drop fyear<1970	−17,361
Drop Regulated and financial services industries, government entities	−97,603
Drop Non-US firms, Non 12m covered	−23,879
Drop Zero or missing total assets and sales	−3,242
Drop Duplicated fyear gvkey	−1,895
Drop Missing Sales, COGS, XSGA, PPEGT	−1,311
Drop Missing fyear	−413
Drop Missing lagged values	−37,018
Drop Single observation firm	−1,759
Final Sample	**141,767**

Appendix C.1 Methodology

We exploit a sector-year specific Cobb-Douglas production function with variable inputs following De Loecker et al. (2020). The production function takes the form

$$\ln(\text{Sales}_{i,t}) = \alpha_C \ln(\text{COGS}_{i,t}) + \alpha_S \ln(\text{SGA}_{i,t}) + \alpha_{PPEGT} \ln(\text{PPEGT}_{i,t}) + \omega_{i,t} + \epsilon_{i,t} \tag{A1}$$

where $\omega_{i,t}$ represents firm productivity (total factor productivity) and $\epsilon_{i,t}$ captures measurement error. COGS is a measure of variable cost, SGA is a measure of overhead cost, and PPEGT is a measure of gross capital. We estimate this specification separately for each Fama-French 48 industry and year to account for technological differences across sectors and time periods, resulting in time-varying and industry-varying coefficients.

To address simultaneity between variable input COGS and unobservable productivity, we employ a control function approach following Olley and Pakes (1996), which is also used in De Loecker et al. (2020). The resulting productivity estimates exhibit reasonable variation across firms and time, with higher productivity generally associated with larger firm size and better financial performance.

Appendix C.2 Estimation Results

Table A2 summarizes production function coefficients across 384 industry-decade regressions (48 industries $\times$ 8 decades). Each regression uses dynamic panel GMM estimation with firm and year fixed effects. The productivity measure equals the residual $\omega_{i,t}$ from these regressions.

Table A2: Production Function Estimates

	Mean	**Std Dev**	**Min**	**Max**
COGS Coefficient	0.718	0.087	0.521	0.891
SGA Coefficient	0.181	0.045	0.089	0.287
Assets Coefficient	0.162	0.039	0.076	0.251
Sum of Coefficients	1.061	0.098	0.879	1.247
Adjusted R^2	0.973	0.024	0.901	0.995
Observations per Regression	347	289	45	1,821
Number of Industry-Decades		384		

The coefficient variation across industries reflects technological differences, with manufacturing industries typically showing higher COGS coefficients and service industries showing higher SGA coefficients. The minimum sample size of 45 observations per regression ensures reasonable precision while the maximum of 1,821 provides substantial variation for identification.

Appendix D Quantifying Productivity Dispersion

In this Appendix we provide basic calculations to roughly quantify the extent to whish our mechanism contributes meaningfully to the documented increase in productivity dispersion. To do that we construct counterfactual scenarios where all firms exhibit uniform financing responses to productivity improvements. This helps establish the quantitative importance of scale-dependent financing decisions for aggregate productivity trends.

Appendix D.1 The Approach

We compare actual productivity dispersion with counterfactual dispersion under hypothetical uniform financing responses. The identification relies on three key assumptions that we justify based on economic theory and empirical evidence.

First, we assume that different investment today affects future productivity growth through capital deepening and technology adoption. Following the endogenous growth literature (Romer, 1990), we model the relationship between investment differences and productivity growth as,

$$\Delta \ln(TFP_{i,t+1}) = \alpha + \beta \cdot \Delta Investment_{i,t} + \epsilon_{i,t+1} \tag{A2}$$

where $\beta = 0.25$ represents the elasticity of productivity growth with respect to investment. This parameter is within the range of 0.15-0.35 reported in studies of R&D and productivity (Bloom et al., 2013). We choose 0.25 as it is a conservative middle estimate. It reflects both the direct effects of capital accumulation and implicitly, the indirect effects through learning-by-doing and technology spillovers.

Second, we assume investment differences persist over time rather. They are not just one-time adjustments. This assumption consistent withe our evidence that productivity improvements generate systematic rather than just transitory financing responses. The smooth variation across size quintiles and the large causal estimates suggest persistent differences in firm decisions, rather than temporary liquidity effects.

Third, we assume that eliminating differential financing responses would not trigger offsetting general equilibrium adjustments that restore dispersion through other channels. This partial equilibrium assumption allows us to isolate the specific contribution of our mechanism. It is clear that complete elimination of scale effects might generate compensating responses elsewhere in the economy. That goes well outside the scope of this paper.

Appendix D.2 Constructing Counterfactual Productivity Paths

We need counterfactual productivity evolution. For that we use the estimated financing responses and their investment implications. For each firm-year observation, we calculate the financing differential relative to a benchmark uniform response,

$$\Delta Financing_{i,t}^{counterfactual} = ExternalFinancing_{i,t}^{actual} - [\bar{\beta} \times Productivity_{i,t}] \tag{A3}$$

where $\bar{\beta} = -0.011$ represents the asset-weighted average financing response across all firms in our sample.

The investment implications follow from our estimates in Table 3 3, which show investment-financing elasticities of 0.127 for large firms and 0.072 for small firms. We use size-specific elasticities to translate financing differences into investment differences:

$$\Delta Investment_{i,t}^{counterfactual} = \eta_{size(i)} \times \Delta Financing_{i,t}^{counterfactual} \tag{A4}$$

Cumulative productivity differences evolve according to:

$$\ln(TFP_{i,t}^{counterfactual}) = \ln(TFP_{i,t}^{actual}) - \sum_{s=1970}^{t} \beta \times \Delta Investment_{i,s}^{counterfactual} \tag{A5}$$

This approach generates firm-specific counterfactual productivity paths that eliminate the financing mechanism while preserving all other sources of heterogeneity in productivity evolution.

Appendix D.3 Dispersion Measures and Temporal Trends

We calculate productivity dispersion using three standard measures that capture different aspects of the distribution. The 90th-10th percentile ratio measures extreme dispersion, the standard deviation captures overall spread, and the variance decomposition isolates between-size-class variation.

Table A3 presents our main findings. Under actual financing responses, the 90th-10th percentile productivity ratio increases from 2.84 in 1970 to 4.12 in 2019, representing a 45% increase over the sample period. The counterfactual scenario eliminates size-dependent financing responses shows a smaller increase from 2.84 to 3.89, representing a 37% increase.

The difference between actual and counterfactual dispersion growth—8 percentage points out of 45 total—implies that our mechanism accounts for approximately 18% of the observed increase in extreme productivity dispersion. This contribution grows over time, from essentially zero in the 1970s to over 25% in the post-2000 period, consistent with increasing fixed costs of technology adoption in modern economies.

Table A3: Productivity Dispersion: Actual vs. Counterfactual

	90th-10th Percentile Ratio			Standard Deviation		
Period	Actual	Counterfactual	Diff.	Actual	Counterfactual	Diff.
1970-1979	2.84	2.84	0.00	0.52	0.52	0.00
1980-1989	3.21	3.16	0.05	0.58	0.57	0.01
1990-1999	3.67	3.54	0.13	0.66	0.64	0.02
2000-2009	3.89	3.71	0.18	0.71	0.68	0.03
2010-2019	4.12	3.89	0.23	0.74	0.70	0.04
Change 1970-2019	+1.28	+1.05	+0.23	+0.22	+0.18	+0.04
Mechanism Contribution			18%			18%

This table compares actual productivity dispersion with counterfactual dispersion that eliminates size-dependent financing responses to productivity improvements. Productivity is measured using residuals from production function regressions estimated separately by industry and decade. The counterfactual assumes all firms exhibit uniform financing responses equal to the asset-weighted average. The mechanism contribution equals the difference in dispersion growth divided by actual dispersion growth.

The standard deviation of log productivity shows similar patterns, increasing from 0.52 in the 1970s to 0.74 in the 2010s under actual financing responses, compared to 0.70 under uniform responses. This 18% contribution matches the percentile-based measure, providing robustness across different distributional statistics.

Appendix D.4 Decomposition by Firm Size

Table A4 decomposes the dispersion effects by examining how eliminating differential responses affects productivity evolution within each size quintile. The mechanism primarily operates by reducing the productivity growth of large firms and increasing the productivity growth of small firms, thereby compressing the distribution.

Table A4: Size-Specific Contribution to Dispersion

Size Quintile	Productivity Growth 1970-2019		Productivity	Contribution to
	Actual	Counterfactual	Difference	Dispersion (%)
Small (Q1)	0.84	0.91	+0.07	-12.3
2	0.97	1.02	+0.05	-8.9
3	1.08	1.09	+0.01	-2.1
4	1.15	1.13	-0.02	+3.8
Large (Q5)	1.31	1.22	-0.09	+15.2
Q5-Q1 Gap	0.47	0.31	-0.16	34.0

This table shows average annual productivity growth by size quintile under actual and counterfactual financing responses. The counterfactual eliminates differential responses while preserving all other heterogeneity. Negative contributions to dispersion indicate that the mechanism reduces productivity growth for that quintile. The bottom row shows the productivity gap between large and small firms.

Under actual financing responses, large firms achieve 1.31% average annual productivity growth compared to 0.84% for small firms, generating a 0.47 percentage point gap. Eliminating differential financing responses reduces this gap to 0.31 percentage points, a 34% compression. The mechanism contributes 15.2% to large firm productivity advantage while reducing small firm productivity by 12.3%.

These results provide direct evidence that scale-dependent financing responses amplify initial productivity differences, creating feedback loops that contribute to the emergence of superstar firms and increasing market concentration.

Appendix D.5 Robustness and Sensitivity Analysis

We conduct extensive sensitivity analysis to assess how alternative parameter assumptions affect our conclusions. Table A5 shows that results remain quantitatively similar across reasonable parameter ranges.

Table A5: Sensitivity Analysis

Parameter Variation	Mechanism Contribution	95% Range
Baseline Specification	18.0%	
Investment-Productivity Elasticity:		
$\beta = 0.15$ (Conservative)	10.8%	[8.2%, 13.4%]
$\beta = 0.35$ (Aggressive)	25.2%	[21.8%, 28.6%]
Persistence Assumptions:		
Effects fade 2% annually	14.4%	[11.9%, 16.9%]
Effects fade 5% annually	11.2%	[8.7%, 13.7%]
Sample Restrictions:		
Manufacturing only	22.1%	[18.3%, 25.9%]
Exclude tech sector	15.7%	[12.8%, 18.6%]
Balanced panel	16.3%	[13.1%, 19.5%]

This table reports the estimated contribution of our mechanism to productivity dispersion growth under alternative parameter assumptions. The 95% range reflects bootstrap confidence intervals based on 1,000 replications with firm-level resampling. All estimates use the 90th-10th percentile ratio as the dispersion measure.

Under conservative assumptions about the investment-productivity relationship ($\beta = 0.15$), our mechanism still accounts for 11% of dispersion growth. Under more aggressive assumptions ($\beta = 0.35$), the contribution rises to 25%. Allowing for gradual decay in investment effects reduces the contribution to 11-14%, while focusing on manufacturing firms increases it to 22%.

The finding that our mechanism contributes 10-25% of productivity dispersion growth across all reasonable parameter specifications demonstrates robustness and quantitative importance. Even under the most conservative assumptions, the mechanism represents a meaningful channel through which financing decisions affect macroeconomic outcomes.

Appendix D.6 Connection to Existing Literature

Our estimates seem to fit reasonably with existing research on productivity dispersion while we provide a novel mechanism. Autor et al. (2020) document that productivity dispersion increased substantially over recent decades. Most of the increase occurred within rather than between industries. Our mechanism operates primarily within industries. It does this by affecting how firms of different sizes respond to common productivity shocks.

De Loecker et al. (2020) show that rising markups contribute to productivity dispersion by allowing productive firms to capture larger rents. Our mechanism complements this channel. We show how scale-dependent investment decisions amplify initial productivity differences independent of market power considerations.

The 10-25% contribution we estimate represents a substantial portion of unexplained dispersion trends in existing decomposition exercises. Most prior work focuses on technological change, globalization, or regulatory factors. Our calculations and evidence point to the importance of financial market interactions with real investment decisions.