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

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Abstract

We document striking differences in small and large firm responses to productivity shocks. A 1% increase in productivity reduces external financing by 0.7% of assets in small firms, but increases it by 3.2% in large firms. This difference affects both the use of external debt and equity. Using state-level R&D tax credits as an instrument, we provide causal evidence that productivity improvements exacerbate this divergence. Small firms reduce external financing by 9.0% and large firms increase it by 5.1%. We explain this evidence using a model in which fixed costs of technology adoption create size-dependent investment thresholds.

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1 Introduction

Consider a firm that receives a positive productivity shock. What should it do? Standard economic reasoning (Lucas Jr, 1978; Hayashi, 1982) suggests that because the firm is now more productive, it should raise funds and use the money to increase investment that exploits the new opportunity. Is that what firms really do? The purpose of this paper is to answer that question. In reality some firms do react in the standard manner, but other firms strongly react in the opposite direction – they return funds to investors and reduce investment. That firm heterogeneity is robust and we show that it can be understood within a basic model of firm financing in which upgrading technology has a fixed cost, so small firms may not be able to spread those costs over enough output.

We offer three main novel findings. First, is that upon receiving a positive productivity shock small and large firms have opposite financing responses. When productivity improves, large firms increase external financing by about 3.2% of assets as suggested by standard economic reasoning. But small firms actually reduce external financing by about 0.7% of assets.

Second, we provide causal evidence of that divergence using state-level R&D tax credits as instrumental variables. We find that the IV estimates are even stronger than the panel regression results. In response to the R&D tax credits, large firms increase external financing by 5.1% , while small firms reduce it by 9.0%.

Third, we provide an explanation for the evidence based on a technology adoption threshold mechanism. In the model this divergence is due to fixed costs of technology adoption. These fixed costs create size-dependent investment thresholds. Large firms can spread fixed costs over more output. For them the investment in upgrading the technology is profitable. Small firms cannot spread the fixed costs over as much output. For them the investment in upgrading technology is unprofitable. But due to the improved productivity they have more cash than previously. So they sensibly return capital to their investors.

Our evidence and interpretation is grounded in basic economic reasoning. But it does depart from a number of ideas suggested by the previous literature. Our perspective is contrary to simple standard neoclassical theory Hayashi (1982). In that model all of the now more productive firms ought to attract more capital. Our perspective is distinct from traditional financing constraint models Fazzari, Hubbard and Petersen (1988). From that point of view the less productive firms might be financially constrained and thus have trouble raising funds. The standard financially constrained idea would not predict that those firms would actively return capital to their investors. Our perspective is distinct from the literature on superstar firms and declining competition (Autor et al., 2020; Philippon, 2019; Covarrubias, Gutiérrez and Philippon, 2020). We point to the fixed costs of technology adoption as a crucial mechanism. It creates sharply different incentives for small firms and for large firms. This divergence need not reflect market power differences and changes.

We provide novel evidence and a distinctive explanation for growing productivity dispersion. We provide a systematic explanation of why small firms might optimally choose not to upgrade technology despite having the capital to do the upgrade. The result is diverging paths.

In order to establish those facts and our interpretation, we start by relating productivity to external financing. When reacting to improved productivity, firm size heterogeneity proves critical. Using panel regressions with firm and year fixed effects, on average firms in the top firm size quintile react to a one standard deviation increase in productivity with a 3.2 % increase in external financing. They then use the extra funds to increase real investment. On average firms in the smallest firm size quintile do not react like that. When they have a one standard deviation improvement in productivity they reduce external financing by 7.4 %. This sharp difference is quite robust across time periods and across industrial sectors.

The panel regressions clearly provide statistically reliable evidence, but is it causal? In order to bolster our causal claim we study the impact of staggered changes in state-level R&D tax credits with varying generosity. Following the reasoning in Wilson (2009); Bloom, Schankerman and Van Reenen (2013); Hombert and Matray (2018) these tax changes provide plausibly exogenous shocks to firm costs and hence to tax-adjusted productivity. This instrument makes sense economically, and it is strong according to econometric tests (Andrews, Stock and Sun, 2019; Keane and Neal, 2023). This is used as an instrumental variable and we find that the effects are have the same signs, but they are even stronger in magnitude than in the regular panel regressions. The consistency of the coefficient signs across alternative econometric tests is reassuring.

The results are statistically strong and appear to be causal, but are they economically large enough to matter? To address this we convert the coefficients into dollars. A typical small firm experiencing a one standard deviation productivity improvement reduces external financing by approximately $2.1 million or 2.0% of assets. This is achieved through a combination of debt repayment ($0.8 million) and reduced equity issuance ($1.3 million). In contrast, a typical large firm with the same productivity gain increases external financing by $15.4 million. This divergence occurs for firms facing similar productivity shocks and operating in the same industry.

The divergence is real, causal, and large enough to matter. What exactly is the underlying economic mechanism? We show that this divergence can easily emerge by using a model based on technology adoption costs within a simplified version of the popular CES demand monopolistic competition approach (Dixit and Stiglitz, 1977; Melitz, 2003). Our model is simplified on several dimensions and we introduce a fixed cost of technology adoption. Fixed costs of technology adoption generate size-dependent investment thresholds. Small firms typically operate below the critical threshold. So they are unable to profitably cover the fixed costs a technology upgrade. So what else to do with the inflow of funds from the productivity improvement? Reward the investors using the extra cash. Large firms in contrast, commonly operate above the threshold. For them it is profitable to raise additional funds to pay for technology investment when productivity has improved. So large firms do raise funds following a positive productivity shock.

Our evidence suggests a possible reinforcing cycle. There have been growing differences between small and large firms (Crouzet and Mehrotra, 2020). When large firms become more productive, they invest in becoming even more productive, creating a self-reinforcing cycle through technology adoption. Firms in the largest quintile increase external financing by 0.3% of assets for each standard deviation increase in productivity, while investing in improved technology. In contrast, small firms, despite achieving productivity gains, reduce external financing by 2.0% of assets, foregoing technology upgrades. This pattern persists. Highly productive firms are four times more likely to remain highly productive compared to low-productivity firms moving up (64.5% versus 16.7% probability). Moreover, Table 1 reveals that this divergence has increased over time - the productivity gap between the highest and lowest quintiles was 30% larger in 2010-2019 compared to 1970-1979. These systematic differences in how small and large firms respond to productivity improvements suggest a natural mechanism through which initial size differences become amplified through differential technology investment.

Our findings have potentially important implications for policies aimed at promoting business dynamism and productivity growth. We observe actual policies focus on improving small firms' access to capital through lending programs or public market reforms. Think of the Small Business Administration (https://www.sba.gov/) altogether. However, we find that many small firms with high productivity actually choose not to raise capital for technology investment even when they could. Their actions are consistent with binding constraint being the fixed costs of adoption, not traditional financing constraints. From this perspective policies aimed at alleviating financing constraints may be less effective than one might hope. Policies targeting adoption costs directly might be more effective. Of course, it is still necessary to do cost-benefit calculations before undertaking targeted tax incentives or technical assistance to help the small firms.

2 Related Literature

Our facts do not fit directly with standard neoclassical theory of corporate investment (Hayashi, 1982). But they also do not naturally fit within several popular alternatives. Are they due to traditional financing constraints Fazzari, Hubbard and Petersen (1988)? Financial constraints would normally imply that less productive firms have trouble raising funds. They do not imply that more productive small firms actively return it.

Suppose that financing constraints were the key driver. Then less productive firms would be unable to raise desired capital. But in fact we show something stronger. Small firms actively choose to return capital precisely when their productivity is high. That is not a traditional binding financing constraint effect. Suppose instead that output market power or industry concentration were the key drivers. It would then be very hard to explain why small firms reduce both debt and equity financing when their productive efficiency improves. Even a monopolist reacts to lower costs or increased demand, by producing more.

Our analysis contributes to several strands of the literature. We organize these connections in terms of the following categories: the productivity-financing relationship, market power and concentration, and technology adoption. Our paper provides as size-dependent threshold mechanism that is a fundamentally different way of thinking about productivity and financing patterns when constrasted with traditional neoclassical models (Hayashi, 1982) and also when constrasted with traditional financing constraint models (Fazzari, Hubbard and Petersen, 1988).

Productivity and External Financing. Many papers have implications for how productivity affects firms' financing decisions, notably (Gomes, 2001; Hennessy and Whited, 2007). A common prediction is that more productive firms should attract more capital since they have better investment opportunities (Lucas Jr, 1978; Hayashi, 1982). We find evidence supporting this prediction for large firms. However, we find that small firms do the opposite. They systematically return capital to investors when their productivity rises. This novel finding contrasts sharply with the common assumption of a uniformly positive relationship between productivity and net external financing. A pure representative firm model is not designed to capture this kind of difference among firms that coexist. Empirical studies that exclude small firms through a range of data filter criteria will likely not find this result because many of the small firms are being removed by the 'data cleaning' process.

The implication of this divergence between small firms and large firms is that it provides a fundamentally different way to think about results that might casually be thought to reflect financing constraints, (Fazzari, Hubbard and Petersen, 1988; Cooley and Quadrini, 2001; Whited, 1992). If financing constraints were central, then less productive firms might be unable to raise desired financing. However, standard forms of financing constraints cannot explain why small firms would actively choose to return capital to investors at the time that their productivity is particularly good. We both predict and document such actions by small firms. Our fixed cost mechanism provides a novel economic rationale for why optimal financing can decline with productivity.[1]

Market Power and Industry Evolution. The literature on superstar firms has emphasized the importance of a growing difference between small and large firms (Autor et al., 2020; Hsieh and Rossi-Hansberg, 2023; Ayyagari, Demirgüç-Kunt and Maksimovic, 2024). Much of that literature emphasizes declining competition and rising markups (Philippon, 2019; Gutierrez and Philippon, 2017). We instead highlight the importance of fixed costs of technology adoption. It creates divergent incentives, causing small and large firms to respond differently to productivity improvements even absent differences in market power.

A key distinction from Doraszelski and Jaumandreu (2013) is our focus on how fixed costs affect financing rather than just R&D decisions. They study uncertainty in the R&D process. We show that technology adoption costs create size-dependent financing thresholds that amplify initial differences between firms. So we offer a new explanation for growing productivity dispersion that does not rely on changes in competition.

Technology Adoption and Fixed Costs. The idea that fixed costs might affect adoption of new technology is itself not new Hall (2004). What is new is the connection to corporate use of finance and hence to investment more broadly. Our model of technology adoption differs from standard models in the innovation literature such as (Klette and Kortum, 2004; Akcigit and Kerr, 2018). They study the innovation process itself. We study how fixed adoption costs create divergent incentives across the firm size distribution. This size-dependent threshold mechanism is distinct from papers on lumpy investment (Cooper, Haltiwanger and Power, 1999; Khan and Thomas, 2008). Those

[1] It is of course possible to redefine financing constraints to mean fixed costs, and then claim that fixed cost effects are financing constraints. Of course, the vacuous nature of this kind of redefining 'financing constraints' was criticized by Kaplan and Zingales (1997).

papers do not study the interaction among productivity, firm size, and financing choices.

Eisfeldt and Papanikolaou (2013) study how organizational capital affects firm boundaries. They consider productivity differences across firms. But they do not examine how technology adoption costs create systematic variation in financing responses. Our model shows that these costs generate natural size thresholds that rationalize otherwise puzzling patterns in external financing.

Our modeling approach differs from models focused primarily on financial frictions (Gomes, 2001; Hennessy and Whited, 2007) in that we show how fixed costs of technology adoption naturally create regions where small firms optimally choose to return capital rather than being constrained from raising it. This distinction is important because the empirical evidence shows small firms actively returning capital rather than simply being unable to raise funds.

We differ from models focused primarily on innovation processes (Klette and Kortum, 2004; Akcigit and Kerr, 2018). Those papers study the R&D investment decision in detail but do not examine how fixed costs create divergent financing patterns across the firm size distribution. Our mechanism explains why small and large firms make systematically different financing choices even when facing similar productivity improvements.

Overall our key contribution to demonstrate the importance of fixed costs of technology adoption in creating divergent financing responses between small and large firms. Unlike existing work focused on financial constraints, market power, or innovation processes, we provide a unified framework. We explain why small firms return capital when productivity rises; show how size-dependent thresholds amplify initial differences; generate novel predictions about financing patterns, provide causal evidence using R&D tax credit variation

Our mechanism has potentially important implications for understanding growing productivity differences across firms. Previous work studies barriers preventing small firms from raising capital. We show that many small firms optimally choose not to upgrade technology even when they could obtain financing if they tried to do so.

Our results speak directly to current policy debates about declining business dynamism and growing productivity dispersion. Unlike explanations based on rising market power or tightening financial constraints, our findings suggest the presence of deeper issue. Small firms often find technology upgrades unprofitable even absent such barriers. So policies focused solely on 'improving access to capital' may have rather limited effects unless the fixed costs of adoption can be dealt with in some way.

3 Data

We study Compustat/CRSP Fundamentals Annual data from 1970 to 2020. To start with there are 326,248 firm-year observations. Several standard filters are applied to ensure data quality and comparability with previous studies. First, we exclude financial firms (SIC codes 6000-6999) and regulated utilities (SIC codes 4900-4949) due to their distinct regulatory environments and financing patterns. This removes 97,603 observations. Next we exclude non-U.S. firms and firms not following standard 12-month fiscal calendars at a cost of 23,879 observations. Then we remove observations with missing or negative values for total assets and sales when then costs 3,242 observations.

For the productivity estimation, we require non-missing values for our three key production inputs. These are cost of goods sold (COGS), selling, general and administrative expenses (SGA), and total assets. We require complete data on external financing variables as in Frank and Goyal (2009). These data requirements, combined with the removal of duplicate firm-year identifiers, reduce our sample by 23,118 observations. The final sample contains 159,214 firm-year observations representing 13,847 unique firms over the 51 years.

The median firm in our sample remains is listed for 11.5 years with considerable variation in survival times. The 25th percentile of listing duration is 4 years, while the 75th percentile is 16 years. This variation reflects both firm entry and exit as well merger activity. Firms exit our sample through several methods including mergers and acquisitions (49% of exits), bankruptcy (8%), going private (6%), and other reasons (37%).

We construct our financing variables as in Frank and Goyal (2009). To measure state-level R&D tax credits, we use data from Wilson (2009) updated through 2020. This gives us the timing and magnitude of credit rates for all U.S. states that implemented such tax credit programs. We match firms to states based on headquarters location from Compustat. All continuous variables are winsorized at the 1st and 99th percentiles. Financial variables requiring a price deflator use the GDP deflator from the Federal Reserve Economic Data (FRED) database.

To verify robustness to sample selection choices, we conduct our main analyses on several alternative samples. These are (1) firms present for at least 5 consecutive years, (2) firms with above-median market capitalization, and (3) balanced panels. Our main findings regarding the relationship between firm size, productivity, and financing decisions are quite stable across these alternative samples. So sample construction issues do not appear to be driving our results.

Our data is for public firms. These companies account for over 30% of private non-residential fixed investment in the U.S. economy. Moreover, the systematic differences we document between small and large firms' financing responses to productivity improvements appear robust across various subsamples, time periods, and industry classifications, suggesting they reflect fundamental economic forces rather than artifacts of sample selection.

Table 1 presents key firm characteristics over our 1970-2020 sample period. The data reveals three major patterns in the U.S. corporate sector. First, average productivity increased markedly from 0.61 in the 1970s to 2.40 in the 2010s, indicating substantial technological progress. Second, external financing intensity peaked in the 1990s at 11.3% of assets during the tech boom before moderating to 7.5% in recent years. Third, the composition of external financing shifted. The equity share rose while debt reliance declined.

The divergence between small and large firms shown Figure 1. Large firms (top quintile by assets) saw steady productivity growth. Small firms (bottom quintile) showed relatively modest gains. This divergence increased post-2000. The productivity gap between size groups widening by 0.5 standard deviations. The financing patterns reinforce this divide. Large firms maintained stable access to external capital, while small firms experienced greater volatility and overall declines in financing flows.

In the Appendix Table A.2 documents substantial and growing size dispersion. The gap between mean assets ($2.1 billion) and median assets ($192 million) reflects increasing concentration of production at large firms. The share of total assets at the largest quintile rises from 70% in the 1970s to 89% in the 2010s. This rising concentration coincides with different financing strategies across firm sizes. Equity issuance was 13% of assets for small firms versus just 2% for large firms.

Our data covers the major sectors of the U.S. economy. There are eight industries/sectors that account for 76% of aggregate market capitalization. The business services is the largest segment (11.2% of firms), followed by retail (6.9%) and electronic equipment (6.8%). This composition has remained relatively stable. Of course technology sectors have gained share at the expense of traditional manufacturing over our sample period.

The evolution of the firm size distribution reveals increasing concentration of assets at large firms within the U.S. corporate sector. The share of total assets controlled by the largest quintile of firms grew from 80% in 1970 to 89% in 2020. Much of this increase occurring since 2000. This concentration is particularly pronounced in sectors that appear to be characterized by high fixed costs and strong network effects.

The relationship between fixed costs and firm behavior is particularly striking. Sectors with higher estimated fixed costs, such as electronic equipment ($\phi/AT = 0.183$) and machinery ($\phi/AT = 0.967$), show greater divergence between small and large firms. This is true both for productivity and for the financing patterns. Industries like wholesale trade with lower fixed costs ($\phi/AT = 0.071$) exhibit more modest size-based differentiation. This systematic variation supports our core idea that fixed costs of technology adoption create divergent incentives across the firm size distribution.

These industry-level patterns provide three key insights for our analysis. First, the relationship between firm size and productivity responses is not merely an artifact of industry composition but reflects fundamental economic forces that operate within industries. Second, the strength of these relationships varies predictably with industry characteristics, particularly fixed costs. Third, these patterns have persisted and even intensified over time despite substantial changes.

4 Empirical Strategy and Baseline Evidence

In this section, we explain our empirical approach to investigating the impact of productivity on financing decisions for firms of varying sizes. The initial task is to estimating firm-level productivity. That is used to examine the baseline relationship between productivity and external financing. Once that is in hand we explore how this relationship varies across the firm size distribution.

4.1 Productivity Estimation

There is a large long-standing literature estimating firm productivity (Griliches and Mairesse, 1998; Ackerberg, Caves and Frazer, 2015; De Loecker and Syverson, 2021). For our purpose we need a method that can be readily applied to a broad set of publicly traded firms. For those firms we have standard corporate accounting data. So we use that as the data and follow the production function estimation literature (Ackerberg, Caves and Frazer, 2015; De Loecker and Syverson, 2021; Bond et al., 2021) while adapting these methods to our corporate finance data. Since accounting data is measured in dollars rather than physical units, our productivity estimates are revenue-based.

Our baseline approach models the relationship between output (sales) and three key inputs.

$$\ln(Sales_{it}) = \alpha_C \ln(COGS_{it}) + \alpha_S \ln(SGA_{it}) + \alpha_{AT} \ln(Assets_{it}) + \omega_{it} + \epsilon_{it} \tag{1}$$

where $COGS_{it}$ represents cost of goods sold, SGA_{it} captures selling, general and administrative expenses, and $Assets_{it}$ measures total assets. The error term includes productivity ω_{it} and measurement error ϵ_{it}. The residual term ω_{it} is our measure of productivity. This is similar to De Loecker, Eeckhout and Unger (2020) except that we use total assets rather than just property plant and equipment as the third factor. Our reason is that all of the assets that a firm uses have an opportunity costs. The use of total assets instead of property, plant and equipment generates a broader measure of the firm's asset use. It also allows us to include service industries and other sectors that make less use of tangible fixed assets.

Table 2 provides estimates of our production function using several well established econometric methods for firms from 1972 to 2019. The basic OLS estimates in column (1) show that COGS has the largest coefficient (0.657). So a 1% increase in COGS is associated with approximately a 0.66% increase in sales. SGA and total assets have smaller but still significant coefficients at 0.178 and 0.234, respectively. The model captures most of the variation in the data.

Firm fixed effects may matter. To address this, column (2) reports first-difference estimates. The coefficients remain fairly stable compared to the levels estimation. A 1% increase in COGS associated with a 0.567% increase in sales. In this specification SGA and total assets contribute 0.203% and 0.203% respectively. This stability is very reassuring, particularly when compared to estimates of traditional capital and labor productivity models. As stressed by Griliches and Mairesse (1998) first differencing of capital and labor productivity models commonly generates sharply different parameters.

Column (3) develops the first-difference model by adding input levels as extra control variables. If the difference model fits well, then the coefficients on the first-differenc emodels ought to be largely the same as in column (2). In fact the estimated coefficients on the differenced variables remain very stable. The level variables are statistically sigificant, but they have parameter estimates that are fairly close to zero, and the model has almost no improvment over column (2) in the sense of the variation explained. Column (4) uses the Blundell and Bond (1998) dynamic panel GMM approach. This addresses potential simultaneity between productivity and input choices. It does this by including lagged dependent variables along with suitable instruments. The coefficient on lagged output (0.707) shows substantial persistence in firm production. The input coefficients are smaller than in the OLS specification.

Column (5) uses the famous Olley and Pakes (1996) control function method. The resulting parameters are quite close to those reported in column (1). Generally similar results are obtained in untabulated estimates using the approaches suggested by Levinsohn and Petrin (2003) but with our accounting data as the factors. Overall, Table 2 provides reassurance that the 3 accounting factors are reasonable.

Several aspects of our approach deserve emphasis. In the Internet Appendix Table A.3 we estimate the production function separately for each of the Fama-French 48 industries, in each decade. Then we average. This allows for technological differences across sectors and time. This flexibility helps control for any changes in accounting standards or variation over time in reporting practices that might affect how inputs are measured. As can be seen in that Table the parameter estimates done in this way are quite similar to those obtained in Table 2.

The very high R-squared value of 0.964 in column (1) says that our three-factor model captures the main inputs that determine output variation. Even the first difference specification has an R-squared remains relatively high at 0.599. The stability of coefficients across specifications supports the robustness of our approach to estimating productivity. This is important since having a good productivity measure is critical for our subsequent analysis.

4.2 Productivity and External Financing - Baseline Estimates

We now have estimates of firm-level productivity for each year. We now test its relationship with external financing decisions by firms. We use a panel regression specification where $y_{i,t}$ represents external financing scaled by assets, $Prod_{i,t}$ is our productivity estimate, $X_{i,t}$ includes standard controls from Frank and Goyal (2009), and η_i and δ_t capture firm and year fixed effects.

$$y_{i,t} = \beta_0 + \beta_P Prod_{i,t} + \beta_S Size_{i,t} + \beta_{PS} Prod_{i,t} * Size_{i,t} + \beta_x X_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t} \tag{2}$$

Table 3 presents the baseline results. The critical finding is that on average productivity improvements are associated with **reduced** external financing. In Column (1), a one standard deviation increase in productivity means a 0.7 percentage point reduction in external financing ($t = -14.4$). This negative relationship appears consistently across specifications. It applies to both debt and equity parts external financing. Column (2) shows that higher productivity is associated with lower net debt issuance by 0.25 percentage points ($t = -10.8$), while Column (3) reveals an even stronger negative relationship with net equity issuance of 0.4 percentage points ($t = -12.3$). In all three columns we find that larger firms, as measured by $Log(Assets$ use more external financing.

The critical fact is this negative average relationship between productivity and financing. It presents a puzzle from the perspective of standard theory. Commonly we expect more productive firms to attract more capital. After all, the higher productivity means that they can generate higher returns on investment (Hayashi, 1982). Financing constraint models suggest a related intuition. The less productive firms might be unable to raise desired funding (Fazzari, Hubbard and Petersen, 1988). That again would suggest a positive relationship.

Finding such a basic disconnect between the usual theory and this evidence points to a need to figure out whether this average effect is really masking important heterogeneity. Table 3 already suggests that firm size might play an important role. It is of course well known that larger firms typically have easier access to capital markets (Frank and Goyal, 2024). So we turn next to see if this negative average relationship is primarily driven by small firms.

5 Size-Dependent Effects: The Diverging Paths

Motivated by the originally surprising negative coefficient on productivity, we now investigate the impact of firm size in greater detail. In Table 3 we control for firm size, but we in effect impose the restriction that there is a common coefficient on productivity for firms of different sizes. That common coefficient restriction might not be true.

5.1 Firm Size and External Financing

To examine this we sort firms into size quintiles and then run individual productivity regressions in each quintile. This permits productivity to affect external financing differently for firms of distinct sizes. Table 4 presents results from estimating the following specification separately for each size quintile.

$$y_{i,t} = \beta_0 + \beta_P Prod_{i,t} + \beta_x X_{i,t} + \eta_i + \delta_t + \epsilon_{i,t} \tag{3}$$

Panel A examines total external financing. Panel B examines net debt issues. Panel C examines net equity issue.

The results in Table 3 demonstrates this variation in fact is important. Panel A shows a striking pattern in total external financing. Firms in the smallest quintile have average assets of $20 million. For them a one standard deviation increase in productivity reduces external financing by 2.1 percentage points of assets ($t = -7.9$). Moving across the size quintiles, as firm size increases this negative effect steadily gets smaller. In the largest size quintile (average assets of $8.76 billion), the relationship reverses altogether. For the large firms productivity improvements increasing external financing by 0.3 percentage points ($t = 3.1$). In other words, the large firms behave as traditional economic reasoning suggests. Given how large the top quintile firms are, the actions of these firms is particularly important for the aggregate economy.

The economic magnitude of this difference is large. Consider two firms that both experience a one standard deviation productivity improvement. From Table 3, Panel A, Column 2 (Small Firms), we see that a one standard deviation increase in productivity reduces external financing by about 2.0% of assets (coefficient -0.021 with t-stat -7.9). The average total assets for firms in the smallest quintile is about $20 million. So the dollar impact calculation is 2.0% × $20 million = $0.40 million. For Large firms consider Column 6. A one standard deviation increase in productivity increases external financing by 0.3% of assets (coefficient 0.003 with t-stat 3.1). The average total assets for firms in the largest quintile is $8,756 million. So the dollar impact calculation is 0.3% × $8,756 million = $26 million. The difference in percentage points between small and large firms is thus about 0.3% - (-2.0%)) = 2.3 percentage points.

In Table 1 we see that the overall average external finance is 0.080 of assets. The 2.3 percentage point difference represents 2.3/8.0 = 29% of mean external financing. Panels B and C decompose this external financing into net debt and net equity issues. Panel B shows that small firms reduce net debt issuance by 0.4 percentage points ($t = -3.0$). Large firms increase net debt by 0.2 percentage points ($t = 2.9$). Panel C reveals that the effects on the use of equity are, if anything even stronger that the effects for debt. Small firms reducing net equity issuance by 1.4 percentage points ($t = -6.1$) and large firms increasing it by 0.1 percentage points ($t = 2.8$).

These results provide strong evidence that firm size alters how firms respond to productivity improvements. That effect is not like an intercept term. Suppose that productivity increases. Small firms systematically reduce external financing. They do this by both debt repayment and reduced equity issuance. Large firms do the opposite. They raise additional capital through both debt and equity channels. There are more smaller firms than big ones. But the big ones are more important for the aggregate performance of the economy.

The differences across firm size quintiles can help explain the negative average relationship we found earlier. It also opens the door to motivating our model in Section 7. In that model the fixed costs of technology adoption create size-dependent investment thresholds. Those thresholds can explain why small and large firms make such sharply different financing choices when their productivity improves. In the model small firms may find technology upgrades unprofitable despite higher productivity. So they take advantage of improved cash flows to return funds to their investors. Large firms on the other hand can spread fixed costs over more output. For them the technology investment may be attractive. That in turn may induce them to raise additional financing. Hence, the diverging paths.

5.2 External Financing and Investment

Table 5 provides evidence about the important link between external financing and investment decisions for firms of different sizes. This table is essential to our perspective as it is a central link in the causal chain of our model. Productivity improvements affect external financing decisions, which in turn influence investment behavior. The table thus provides empirical evidence on a critical link in our mechanism. When a firm has extra external financing it increases investment. IF a firm has negative external financing it would reduce investment. In Table 5 we permit these connections to be different for firms in distinct size quintiles. We do not impose a common coefficient.

Panel A presents the relationship between external financing and investment across firm size quintiles. The results show a very consistent positive relationship. Firms that raise more external capital invest more. The coefficient in column (1) indicates that a one percentage point increase in external financing (as a proportion of assets) is associated with a 0.077 percentage point increase in investment. This relationship holds across all size quintiles. The coefficients ranging from 0.067 for small firms to 0.088 for large firms. This relationship is surprisingly similar across size categories.This indicates that when firms obtain external financing, regardless of size, they tend to use it for investment purposes. The effect is somewhat stronger for large firms than for small.

Panel B provides a more refined test of our theoretical framework. It provides estimates of how productivity-driven changes in external financing affect investment. We use the fitted values of external financing based on productivity shocks (from Table A.4) as the independent variable. This helps isolate the component of external financing that is specifically attributable to productivity changes. It thus helps us to trace the complete causal path from productivity to financing to investment.

In Panel B we see that across all firm sizes, productivity-driven external financing has a stronger effect on investment (0.097) than raw external financing (0.077). So capital raised in response to productivity changes is particularly likely to be used for investment. The effect is particularly strong for larger firms (coefficient of 0.124 for the largest quintile) when compared to small firms (0.073 for the smallest quintile). This difference in the strength corresponds readily to our model prediction. Large firms raising external finance following productivity improvements, often do so to fund investment in technology upgrades. Small firms that reduce external financing also reduce investment.

These findings complete an important part of our empirical story. We now have the empirical link from productivity to external financing, and the link from external financing to firm investment. We have shown how these connect to firm size.

6 Causal Identification Using R&D Tax Credits

To establish causality, we exploit staggered adoption of state R&D tax credits as plausibly exogenous shocks to the cost of productivity enhancement. Our identification strategy leverages both timing variation in credit adoption across states and differences in credit rates. We are following Wilson (2009); Hombert and Matray (2018).

The first-stage relationship between tax credits and productivity is estimated by,

$$Prod_{i,t} \times R\&DCost_{i,t} = \gamma_0 + \gamma_{PT} Prod_{i,t} \times TaxCredit_{s,t} + \gamma_P Prod_{i,t} + \gamma_x X_{i,t} + \eta_i + \delta_t + \nu_{i,t} \quad (4)$$

Figure 3 provides visual evidence supporting the identification strategy. Financing patterns show no pre-trends prior to the credit adoption but they diverge sharply afterward. Small firms reduce external financing. Large firms increase it, with effects persisting for at least five years. Event study plots and estimates confirm these visual patterns are statistically significant.

The validity of our instrument rests on state credit adoption being driven by political factors rather than firm-specific conditions. Several pieces of evidence support this assumption. Credit timing is uncorrelated with pre-existing state economic trends. The results are robust to controlling for state-level growth. The effects appear only for R&D-intensive industries.

This causal evidence strengthens our core finding. Productivity improvements lead small and large firms to make systematically different financing choices. The magnified IV estimates suggest these divergent responses reflect fundamental economic forces rather than statistical artifacts.

We use state-level R&D tax credits as an instrumental variable to establish causality in the relationship between productivity and external financing decisions. Our identifying assumptions follow.

Relevance condition. State R&D tax credits must strongly affect firm productivity. We find a strong first-stage relationship (F-statistic of 134.3, well above conventional thresholds), showing the instrument is not weak.

Exclusion restriction. State R&D tax credits must affect external financing decisions only through their impact on productivity, not through other channels. Is this plausible? The timing of tax credit adoption varies across states and appears driven by political factors rather than firm-specific conditions. The staggered implementation across states creates natural variation that is unlikely to be driven by individual firm financing decisions. Credit rates differ substantially across states (as shown in Figure 2). State policymakers typically implement R&D credits for broader economic development goals, not in response to specific financing patterns of resident firms. The effects appear only in R&D-intensive industries. The timing effects seem to line up reasonably. The absence of pre-trends in Figure 3 supports the claim that the tax credit changes represent exogenous shocks The state-year variation provides substantial identifying power that helps isolate the causal effect So this seems plausible.

We do need to acknowledge that it could be wrong. The following ideas could be a source of concern. Firms might relocate headquarters to take advantage of tax credits. This is partially addressed by using the original headquarters location. Other contemporaneous state-level policy changes might correlate with R&D credit adoption. Large firms might have political influence over state tax policy decisions. As best we can tell none of these took place at a level of impact that we have been able to identify such disruptive effects.

Independence assumption. The instrument is supposed to be as good as randomly assigned. Credit timing is uncorrelated with pre-existing state economic trends. Results remain robust when controlling for state-level growth. The placebo tests in Table 9 show no significant effects when using randomized adoption dates. So this seems reasonable.

Table 6 Panel A gives the first-stage regressions of the instrumental variables approach. The dependent variables are the interaction between productivity and R&D cost (first column), and the R&D cost alone (second column). The critical independent variable is the interaction between productivity and state-level tax credits, which serves as our instrument.

In column (1) there is a strong negative coefficient on Productivity×Tax Credit (-0.799). This means that when states offer more generous R&D tax credits, the effective cost of R&D declines strongly for productive firms. This relationship is strongly statistically significant ($t = -11.6$), which is good for a strong first-stage relationship. In the second column, the Tax Credit variable alone strongly predicts lower R&D costs (-0.492, $t = -11.0$).

The high F-statistic (338.101) far in excess of the standard rule of thumb values like 10 or even 100, see Keane and Neal (2023) for more discussion. There is a significant Anderson-Rubin test (p-value = 0.000) confirming that the instrument is strong and relevant. The high R-squared values (0.865 and 0.869) also suggests the first stage explains much of variation in R&D costs.

Panel B of Table 6 provides the central results by comparing OLS estimates (columns 1-3) with instrumental variable estimates (columns 4-6). This is done for three outcome variables: external finance, net debt issuance, and net equity issuance. In the OLS specifications, the interaction between productivity and R&D cost is negative for all financing measures. The statistical significance for external finance (-0.017, $t = -2.0$) and net debt issuance (-0.009, $t = -1.7$) are borderline statistically significant. This is moderately weak evidence that firms reduce their external financing more strongly in response to productivity improvements when they face higher R&D costs.

The use of IV is quite important. The IV estimates in columns 4-6 have much larger coefficients than were found in the OLS estimates. The coefficient on Fitted Productivity$\times$R&D Cost for external finance is -0.135 ($t = -2.5$). It is almost eight times larger than the OLS estimate. Addressing endogeneity through the instrumental variable approach shows the much stronger negative relationship between productivity and external financing in high R&D cost environments.

Importantly the productivity variable by itself is more negative in the IV specifications than it is in OLS estimates. This suggests that the causal effect of productivity on financing reduction is stronger than the raw correlation might suggest. This pattern is true across all three financing measures. It is strongest for external finance as a whole.

Panel C gives results for the heterogeneous effects of productivity on external financing across different firm types. This is done by splitting the sample along two dimensions. We distinguish firm size (small vs. large) and R&D costs (high vs. low).

Start with firms with high R&D costs. Small firms significantly reduce external financing in response to productivity improvements (-0.023, $t = -4.2$). The large firms slightly increase it (0.005, $t = 1.8$), but that is not statistically significant. This divergence is generally consistent with the main findings. It does show that the effect is particularly pronounced in high R&D cost environments, as seems reasonable.

Now consider firms with low R&D costs. Small firms have a positive not significant relationship between productivity and financing (0.373, $t = 1.1$). Large firms have a smaller positive relationship and it is marginally significant (0.012, $t = 1.9$). This means that when R&D costs are low the diverging path effects are relatively weak.

The sharp contrast between small firm responses in high versus low R&D cost environments makes sense under our model mechanism. When those costs are low their effects are weak. It is also worth noticing that the sample sizes are quite different in the high and low R&D cost groups. There are many more observations in the high cost category. This suggests that the R&D cost barrier is likely relatively common among the firms that we are studying.

7 Model

We have a continuum of firms indexed by $i \in [0, 1]$. Demand is modeled using a nested CES (Constant Elasticity of Substitution) framework. The CES aggregator is given by

$$Y^{\frac{\sigma-1}{\sigma}} = \int_0^1 y_i^{\frac{\sigma-1}{\sigma}} di$$

where Y is the aggregate output, y_i is the output of firm i, and σ is the elasticity of substitution.

The corresponding price index is,

$$P^{1-\sigma} = \int_0^1 p_i^{1-\sigma} di$$

where P is the aggregate price index and p_i is the price set by firm i.

Given the price index, the demand for each firm's output is,

$$y_i = Y \left(\frac{p_i}{P}\right)^{-\sigma}$$

The production function for firm i is,

$$Y_i = a_i L$$

where a_i is the firm-specific productivity and L is the aggregate input defined as:

$$L = C^{\alpha_C} S^{\alpha_S} AT^{\alpha_{AT}}$$

Here, C is the cost of goods sold, S is selling and general administrative expenses, and AT represents total assets.

Firms maximize profit,

$$\pi_i = p_i y_i - w_i L_i$$

Taking the first-order condition with respect to p_i,

$$0 = y_i + p_i \frac{\partial y_i}{\partial p_i} - \frac{w_i}{a_i} \frac{\partial y_i}{\partial p_i}$$

Given the demand function, we can derive,

$$-\frac{1}{y_i} \frac{\partial y_i}{\partial p_i} = \frac{\sigma}{p_i}$$

Substituting this into the first-order condition and solving for p_i,

$$p_i = \frac{w_i}{a_i} \frac{\sigma}{\sigma - 1}$$

Substituting the optimal price into the demand function,

$$y_i = (\frac{a_i}{w_i})^\sigma Y P^\sigma \left(\frac{\sigma - 1}{\sigma}\right)^\sigma$$

We can rewrite firm's profit without fixed cost as

$$\begin{aligned}
\pi_i &= p_i y_i - w_i L_i \\
&= p_i y_i - \frac{w_i}{\alpha_i} y_i \\
&= (p_i - \frac{w_i}{\alpha_i}) y_i \\
&= (\frac{w_i}{a_i} \frac{\sigma}{\sigma - 1} - \frac{w_i}{\alpha_i}) y_i \\
&= \frac{1}{\sigma - 1} \frac{w_i}{\alpha_i} y_i \\
&= \frac{1}{\sigma - 1} \frac{w_i}{\alpha_i} (\frac{a_i}{w_i})^\sigma Y P^\sigma \left(\frac{\sigma - 1}{\sigma}\right)^\sigma \\
&= \frac{1}{\sigma - 1} \left(\frac{\sigma - 1}{\sigma}\right)^\sigma Y P^\sigma (\frac{a_i}{w_i})^{\sigma - 1}
\end{aligned}$$

Add fixed cost, the firm's profit is then,

$$\pi_i = \frac{1}{\sigma - 1} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_i}{w_i})^{\sigma - 1} - \phi$$

where ϕ is a fixed cost.

Now consider the technology upgrade decision. Firms can choose to invest in a technology upgrade, increasing their productivity from a_i to $a_i h$, where $h \geq 2$.

If a firm does not upgrade,

$$\pi_i = \frac{1}{\sigma - 1} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_i}{w_i})^{\sigma - 1} - \phi - r(c_0 + e)$$

where c_0 is the initial cash endowment, e is the amount of external financing (negative if distributing cash), and r is the cost of carrying cash or raising external financing.

If a firm does upgrade. The firm need an cost ϕh. Such an investment needs to be financed. Assume for simplicity that the firm will exhaust its cash holdings, and so need to raise money from external investors. We assume that the cost of carrying cash and the cost of raising external financing are the same.

$$\pi_i = \frac{1}{\sigma - 1} (\frac{\sigma - 1}{\sigma})^{\sigma} Y P^{\sigma} (\alpha_i h)^{\sigma - 1} - \phi h - r(\phi h - c_0).$$

Here ϕ denotes the fixed cost per unit of upgrading, and r denotes the financing cost of investment.

If a firm does upgrade,

$$\pi_i = \frac{1}{\sigma - 1} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_i h}{w_i})^{\sigma - 1} - \phi h - r(\phi h - c_0)$$

To find the optimal upgrade level $\hat{h}$, we take the first-order condition of the profit function with respect to h.

$$\hat{h} = \left(\frac{1}{\phi + r\phi} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_i}{w_i})^{\sigma - 1} \right)^{\frac{1}{2 - \sigma}}$$

How does the financing flow connect to productivity? Consider the low productivity threshold. To do that define a_L such that $\hat{h} = 1$.

$$a_L = w \left((\frac{\sigma}{\sigma - 1})^{\sigma} \frac{\phi + r\phi}{Y P^{\sigma}} \right)^{\frac{1}{\sigma - 1}}$$

For $a_i \leq a_L$, firms will not upgrade.

This case, the amount the firm chooses to pay out should be equal to the profit in order to maintain the cash requirement c_0; thus, the cash payout at the beginning is equal to

$$e = -(c_0 - \pi) = -(c_0 - \frac{1}{\sigma - 1}(\frac{\sigma - 1}{\sigma})^{\sigma} Y P^{\sigma} (\frac{\alpha_2}{w})^{\sigma - 1} + \phi)$$

Now consider the high productivity threshold. To do that define $a_U = \max(a_{U1}, a_{U2})$ where

$$\hat{h}(a_i = a_{U1}) = \left(\frac{1}{\phi + r\phi} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_{U1}}{w})^{\sigma - 1} \right)^{\frac{1}{2 - \sigma}} = 2$$

and a_{U2} satisfies the indifference condition between upgrading and not upgrading. **For $a_i > a_U$, firms will upgrade.**

How does that connect to external financing? For firms that upgrade ($a_i > a_U$), the amount of external financing is,

$$e = \left(\frac{1}{\phi} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} a_i^{\sigma - 1} \right)^{\frac{1}{2 - \sigma}}$$

Next consider the productivity and firm size relationship.

The profit for non-upgrading firms follows. For $a_i < a_L$ we have,

$$\pi_i = \frac{1}{\sigma - 1} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_i}{w})^{\sigma - 1} - \phi.$$

The profit for upgrading firms follows. For $a_i > a_U$ we have,

$$\pi_i = (\phi + r\phi) \frac{2 - \sigma}{\sigma - 1} \left(\frac{1}{\phi + r\phi} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} (\frac{a_i}{w})^{\sigma - 1} \right)^{\frac{1}{2 - \sigma}} + r c_0.$$

So we see that there is a positive relationship between productivity and firm size (as measured by profit) in both the low and high productivity regions.

8 Counterfactual Policy Analysis

8.1 Policy to Reduce Fixed Cost

We assume that the firm size distribution is evenly distributed, as shown below, using the mean values of each size quintile from Table 4. For example, 20 is the mean value of the lowest quintile group in Table 4. Therefore, we assume that the lowest size is 0, the 10th percentile is 20 million USD (same unit thereafter), the 30th percentile is 79, and so on. We assume a total of 2,000 firms, with 200 firms in each 10th percentile group. The cutoff values lie between group 2 and group 3, with a value of 154.5= $(79 + 230)/2$.

We next conduct a counterfactual analysis based on our model parameter estimates. We rely on the estimation process, which exploits the size distribution of firms. Without a reduction in fixed costs, the cutoff firm size is 154.5, meaning that firms with total assets exceeding this threshold will upgrade to the new technology.

We consider a policy that reduce fixed cost by 50%. With a 50% reduction in fixed costs, the cutoff total assets decreases to 77.25= $154.5/2$. Before the reduction, the percentage of firms that will upgrade is 60%. After the reduction, the percentage increases to 75% $(= 60\% + \frac{154.5-77.25}{154.5-49.5} * 20\%)$. Therefore, 15% $(= 75\% - 60\%)$ more firms will upgrade if there is a 50% reduction in fixed costs.

Next, we examine the productivity increase in this scenario. The increase in productivity comes from the productivity increase for firms that have already upgraded. It also comes from the productivity increase for firms that newly upgrade.

The formula for the productivity multiplier is

$$\hat{h} = \left(\frac{1}{\phi + r} \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma} Y P^{\sigma} a_i^{\sigma - 1} \right)^{\frac{1}{2-\sigma}}$$

For firms that have already upgraded, the productivity increase is 145% $(= (1/0.5)^{\frac{1}{2-\sigma}})$, corresponding to a 145% improvement in productivity. For firms that newly upgrade, the average productivity increase is 123% $(= (100\% + 145\%)/2)$. Combining these two components, the overall productivity increase is 108% $(= 60\% * 145\% + 15\% * 123\%)$.

The key force driving small and large firms reactions apart is the impact of fixed costs. Suppose that the government creates a policy that directly reduces technology adoption fixed costs. How will that affect firm upgrading decisions and aggregate productivity?

Using the parameter estimates from Table 4 we estimate that on average firms with revenue above $154.5 million find technology upgrades to be profitable. This threshold is between the second and third quintiles of the firm size distribution. In other words firms in quintiles 3-5 upgrade their technology. Firms in quintiles 1-2 do not. So about 60% of the firm upgrade and about 40% do not do so.

Think of a policy that policy that reduces the technology adoption fixed costs by 50%. Under this policy the new upgrade threshold is $77.25 million. This falls in the second quintile. For simplicity, assume a uniform distribution within each quintile. Then approximately 15% of firms would now find upgrading profitable. These are the firms in the upper part of quintile 2. If the policy is implemented the percentage increases to 75% is calculated as $(= 60\% + \frac{154.5-77.25}{154.5-49.5} * 20\%)$. So the policy increases the total percentage of upgrading firms from 60% to 75%.

But the impact of the policy operates through two channels, not one. The extensive margin says that there are firms that adopt the technology under the policy, and they would not have done so without the policy. But there is also an intensive margin. The existing technology upgrading firms also face a lower fixed cost. That can alter their decisions as well. That is about 60% of firms whose investment is potentially altered too.

How does the policy that reduces fixed costs by 50% affect the firms that would have upgraded even without the policy? To calculate that impact note that the productivity multiplier is $\hat{h} = \left(\frac{1}{\phi+r}\left(\frac{\sigma-1}{\sigma}\right)^{\sigma} Y P^{\sigma} a_i^{\sigma-1}\right)^{\frac{1}{2-\sigma}}$.

Using our model's productivity function and estimated parameters, according to the multiplier the 50% reduction in fixed costs results in the existing adopters achieving approximately 45% higher productivity. For firms that have already upgraded, the productivity increase is 145% $(= (1/0.5)^{\frac{1}{2-\sigma}})$, corresponding to a 145% improvement in productivity. For firms that newly upgrade, the average productivity increase is 123% $(= (100\% + 145\%)/2)$. Combining these two components, the overall productivity increase is 108% $(= 60\% * 145\% + 15\% * 123\%)$.

What is the overall impact of the policy? We sum the impact on the two groups. New adopters achieve an estimated 23% productivity gain on average reflecting their position in the transition region. Adding up the effects gives the overall aggregate impact. Aggregate Impact $= (60\% \times 45\%) + (15\% \times 23\%) \approx 31\%$.

This counterfactual highlights three factors. First, fixed cost barriers create discontinuities in technology adoption that can be addressed through targeted policy. Many firms that could benefit from technology adoption are deterred by fixed costs rather than by financing constraints.

Second, policy effectiveness depends on the firm size distribution relative to adoption thresholds. The greatest impact occurs when many firms are positioned just below the threshold, as these firms can be "tipped" into adoption with modest interventions.

Third, the economic returns to fixed cost reduction policies likely exceed those of traditional financing programs. Our empirical evidence shows that many small firms actively return capital when productivity rises, indicating that capital availability is not their binding constraint.

We also need some type of disclaimer. What prevents firms that have nothing to do with this industry from trying to get the money too? We assume that this is adequately policed. In reality that could be hard to do. With many technologies and many firms it is likely to be hard to tell them apart. That would be important in practice, but it goes beyond our current scope of analysis.

8.2 Size-Dependent Policy

We examines two policy interventions. The universal tax credit policy allocates benefits across all five firm size groups, whereas the size-dependent policy targets only smaller firms. For comparability, the total amount of tax credits distributed is assumed to remain constant across both interventions. Notably, productivity improvements are generally greater among larger firms, despite the absence of additional productivity gains for these firms when transitioning from "no upgrade" to "upgrade." Consequently, the relative effectiveness of the two policies remains indeterminate a priori.

Under the universal R&D tax credit policy, we adopt a 50% reduction in fixed costs, as calculated in the previous scenario. This universal 50% reduction in fixed costs requires a total expenditure of 77.25 millions = $100\% * 50\% * 154.5$[2]. Alternatively, if this total amount of tax credits is allocated exclusively to group 1 and group 2, it leads to a reduction in the cutoff thresholds for these firms to 30.9 $= 77.25/(1/0.4)$. In this scenario, all firms in group 2 would upgrade, while 7.5% = $\frac{49.5-30.9}{49.5} * 20\%)$ in group 1 would upgrade.

Before the reduction, 60% of firms were expected to upgrade. After the reduction, this percentage increases to 87.5% $(= 80\% + 7.5\%$. Consequently, an additional (=87.5% - 60%) upgrade under this size-dependent policy. The increase in the number of firms is greater compared to the 15% observed under the universal tax credit policy.

Next, we analyze the productivity increase in this scenario. The productivity gains arise from two sources: the increase in productivity for firms that had already upgraded and the increase for firms that newly upgrade.

For firms that had already upgraded, the productivity increase is 145%. For firms that newly upgrade, the average productivity increase is 123%. Combining these two components, the overall productivity increase is calculated as 52%$(= 12.5\% * 145\% + 27.5\% * 123\%)$.

[2]The unit used here is in millions, but the total mass of firms is assumed to be 1.

Overall, the size-dependent policy, although leading more firms to upgrade, does not result in greater productivity improvement.

The first policy we considered provided a subsidy to all firms – a Universal Policy. Now we consider a more targeted approach – a Size-dependent Policy. For a size-dependent policy we need to be explicit about the size of firms that it applies to, and we assume that this can be correctly verified by the government.

Previously we found a technology adoption threshold of $154.5 million in revenue. Under the more targeted approach we still consider the same $77.25 million subsidey. But now it is assumed to apply only to the 40% of firms in the two smallest quintiles.

For the size-dependent policy, concentrating the benefits on 40% of firms increases the effective subsidy for targeted firms. When allocated efficiently, this reduces their effective threshold to approximately $30.9 million, falling within quintile 1. This enables all quintile 2 firms plus those in the upper portion of quintile 1 to upgrade, raising the percentage of upgrading firms to 87.5%.

The size-dependent policy thus generates a 12.5 percentage point larger increase in technology adoption compared to the universal approach (27.5% versus 15%).

Despite its adoption advantage, the targeted policy generates smaller aggregate productivity gains. *Universal Policy*: Boosts productivity of existing adopters (60% of firms) by approximately 45% and new adopters (15%) by 23%, yielding a weighted aggregate gain of 31%. *Size-dependent Policy*: Provides no benefit to larger firms (60% of firms) while boosting productivity of new adopters (27.5%) by 23%, yielding a weighted aggregate gain of just 6.3%.

This counterfactual suggests a fundamental tradeoff in innovation policy design. While the size-dependent policy increases technology adoption more effectively (87.5% vs. 75%), the universal policy generates substantially larger aggregate productivity gains (108% vs. 34%). But what about costs?

This counterintuitive result stems from the intensive margin effect. The universal policy allows already-upgrading larger firms to benefit from reduced fixed costs. That generates substantial productivity improvements that are foregone under the targeted approach. **These findings suggest that policies exclusively focused on small business support may sacrifice significant economy-wide productivity gains that could be achieved through broader innovation policies.**

These findings have potential implications for programs such as the Small Business Innovation Research (SBIR) program and R&D tax credits.[3] While SBIR-type programs provide targeted

[3] https://www.sbir.gov/

support that may be effective at increasing the number of innovative small firms, broad-based R&D tax incentives that benefit firms of all sizes may generate larger aggregate productivity gains.

9 Conclusion

We document a striking divergence in how small and large firms respond to productivity improvements. Small firms reduce external financing by returning capital to investors. Large firms increase external financing to fund additional investments. Using both panel regressions and instrumental variable approaches with state-level R&D tax credits, we establish that this relationship is causal and economically significant.

This divergence is economically large. A one standard deviation increase in productivity leads small firms to reduce external financing by approximately 0.7% of assets. Large firms increase it by about 3.2%. In dollar terms this is a reduction of $0.4 million for a typical small firm versus an increase of $26 million for a typical large firm. Using R&D tax credits as an instrument reveals even stronger effects, with small firms reducing external financing by 9.0% and large firms increasing it by 5.1%.

We provide a unified account of this divergence using a model in which fixed costs of technology adoption create size-dependent investment thresholds. Large firms can spread these fixed costs over greater output, so they upgrade. Small firms cannot spread these fixed costs as widely, so they rationally return capital to investors when their productivity improves. Unlike the large firms they do not invest in upgrades because they would not generate sufficient returns to cover the fixed costs.

Our findings have several implications. First, our evidence indicates that the growing productivity gap between large and small firms may reflect rational responses to fixed technology adoption costs. They are not due to market failures, nor are they due to traditional financing constraints. Second, our results suggest that policies aimed at improving productivity may have distinct effects across the firm size distribution. If not carefully designed they may exacerbating rather than mitigating the productivity gap.

The counterfactual policy analysis demonstrates this clearly. Size-dependent policies targeting small firms increase the number of firms adopting new technologies. Universal policies that reduce fixed costs across the board generate larger aggregate productivity gains. This perhaps unexpected result is due to the intensive margin effect. The already-upgrading larger firms benefit substantially from reduced fixed costs.

A promising direction would be to study whether similar divergent patterns exist for private firms. Private firms constitute a significant portion of economic activity but face different external financing constraints. This would require data we do not currently have access to.

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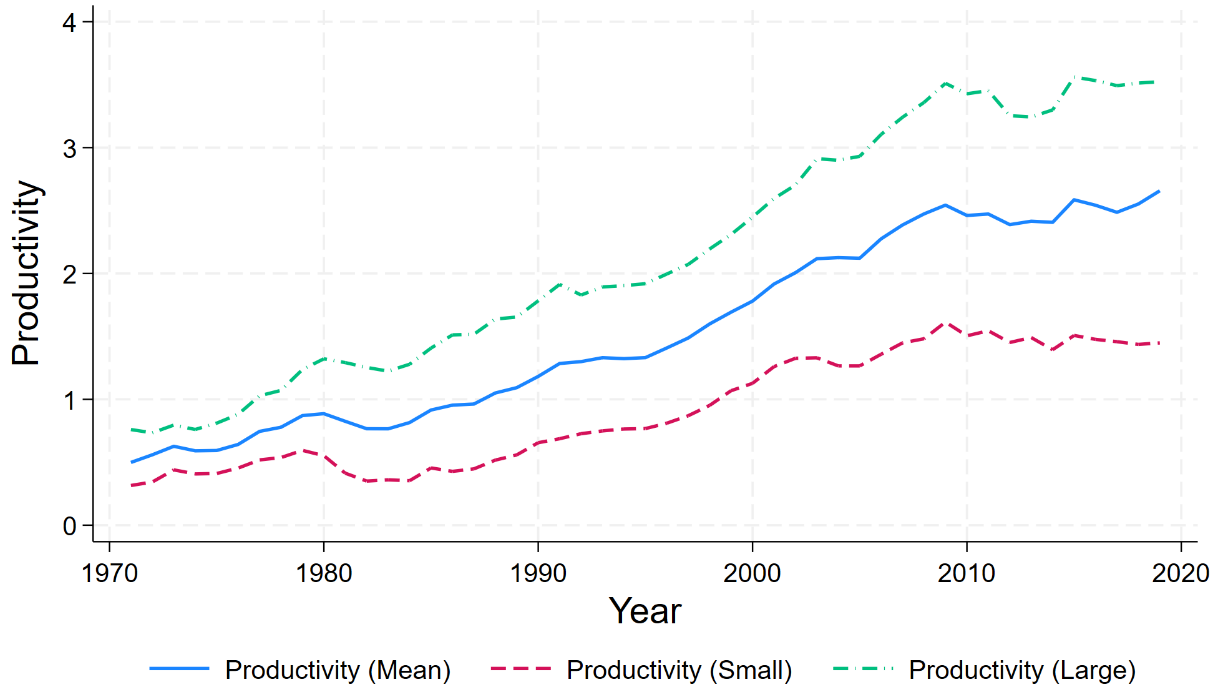
10 Figures

Figure 1: Time Series of Productivity

This figure illustrates the time series of average firm productivity for large, mean size, and small firms. For each year, we calculate the equal-weighted averages of these variables and plot the corresponding time series. Additionally, we divide firms each year into five quintiles based on total assets and compute the equal-weighted averages of these variables for the largest and for the smallest quintile. We also plot the time series of the annual productivity growth rate, separately for the average of all firms, as well as for the largest and smallest quintiles.



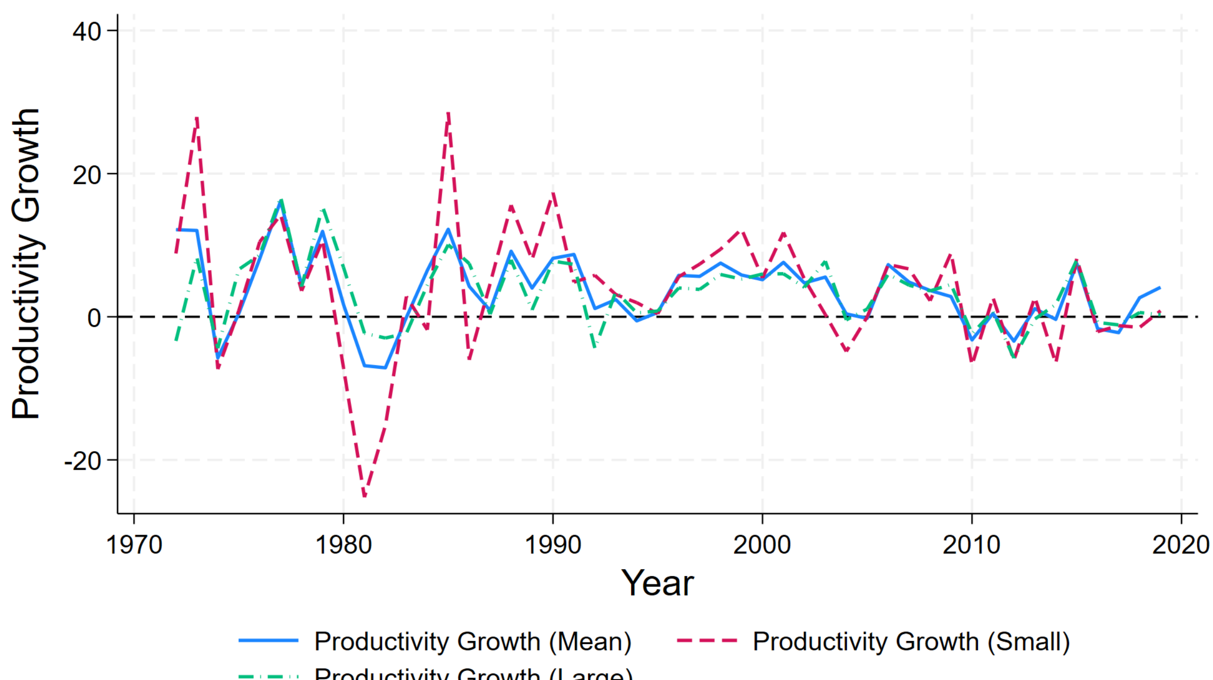


Figure 2: Heterogeneity in R&D Tax Credits

This figure displays state-level average R&D Tax Credits for states that introduce the R&D Tax Credits.

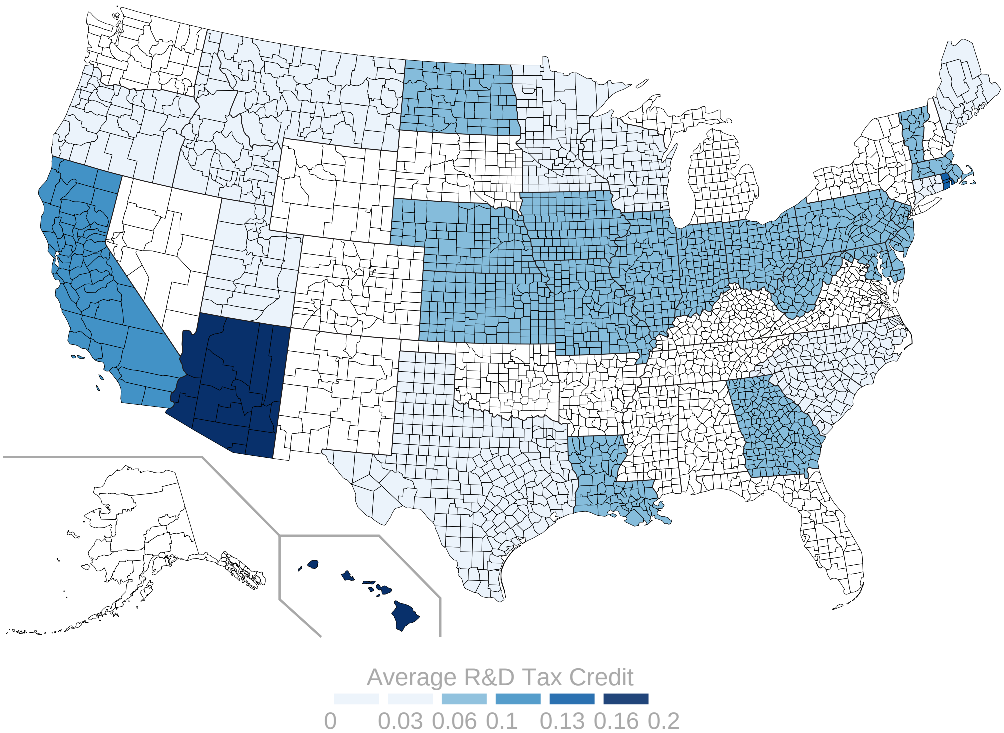


Figure 3: Change After Introducing R&D Credit

This figure presents the time series of average firm productivity, net debt issuance, and net equity issuance relative to the timing of the first introduction of the R&D Credit. For each firm, we calculate the variable Year from Introducing R&D Credit as the difference between the current year and the year when the state where the firm is located first introduced the R&D Credit. A value of "-5" indicates that the observation corresponds to five years before the state first introduced the R&D Credit. For each Year from Introducing R&D Credit, we compute the equal-weighted averages of external financing, net debt issuance, and net equity issuance. Additionally, we provide the values for the 95% confidence interval of the population mean.

11 Tables

Table 1: Summary Statistics Over Time

This table presents the sample means of several key variables from 1970 to 2019. The mean value for each variable is reported.

Decade	(1) All	(2) 1970-1979	(3) 1980-1989	(4) 1990-1999	(5) 2000-2009	(6) 2010-2019
Productivity	1.533	0.670	0.909	1.405	2.148	2.492
External Finance	0.080	0.027	0.076	0.113	0.079	0.075
Net Debt Issue	0.028	0.021	0.032	0.036	0.017	0.027
Debt Issue	0.118	0.062	0.097	0.144	0.119	0.149
Debt Repurchase	0.087	0.041	0.063	0.103	0.097	0.118
Net Equity Issue	0.049	0.005	0.040	0.073	0.058	0.046
Equity Issue	0.061	0.009	0.049	0.083	0.075	0.068
Equity Repurchase	0.012	0.004	0.008	0.010	0.017	0.022
Investment Rate	0.066	0.076	0.084	0.070	0.052	0.048
Asset Growth	0.045	0.033	0.037	0.083	0.018	0.042
Cash	0.158	0.083	0.123	0.151	0.212	0.208
Observations	153969	21507	33007	41050	33763	24642

Table 2: Production Function Estimation

This table presents results of production function estimation for the training sample of firms from 1972 to 2019. Production function is in standard Cobb Douglas form. Output is measured as sales. The input variables are COGS, SGA, and total assets. Capital is measured using gross property, plant, and equipment (PPEGT) deflated by price deflator for investment following İmrohoroğlu and Tüzel (2014). Labor is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration. Column (2) represent OLS regression of all variables in first differences, column (3) adds input level as additional control variables. Column (4) presents the results of a dynamic panel regression using the Blundell and Bond (1998) GMM estimation. The test statistics and p-values for the AR(1) and AR(2) tests, which check for first- and second-order serial correlation in the differenced residuals, are reported. The Hansen J-statistic test and its p-value for overidentifying restrictions are also provided. The estimations include year fixed effects. A few observations are lost due to lagged variables at the beginning of the sample. Column (5) presents the results of control function Olley and Pakes (1996) method, using Total Assets as state variable and Investment as proxy variable.

	(1) OLS	(2) OLS First Diff	(3) OLS First Diff	(4) Dynamic Panel	(5) OP
COGS	0.657***		-0.008***	0.084***	0.682***
	(352.0)		(-12.2)	(4.5)	(137.28)
SGA	0.178***		-0.002***	0.029***	0.188***
	(111.3)		(-3.9)	(5.9)	(33.49)
Total Assets	0.234***		0.006***	0.205***	0.271***
	(121.0)		(8.1)	(20.1)	(31.24)
Δ COGS		0.567***	0.569***		
		(86.1)	(335.0)		
Δ SGA		0.203***	0.203***		
		(34.6)	(157.4)		
Δ Total Assets		0.203***	0.200***		
		(38.8)	(93.2)		
L.Output				0.707***	
				(34.5)	
Obs.	153969	153967	153967	138836	138836
Adj R^2	0.964	0.599	0.600		
Specification Tests:					
AR(1)				-18.29	
				(0.00)	
AR(2)				-4.05	
				(0.00)	
Hansen J-stat				1297.62	
				(0.00)	

Table 3: Productivity and External Finance

This table show estimates of the relationship between firm size and productivity on net financing.

$$y_{i,t} = \beta_0 + \beta_P Prod_{i,t} + \beta_S Size_{i,t} + \beta_{PS} Prod_{i,t} * Size_{i,t} + \beta_x X_{i,t} + \eta_i + \delta_t + \varepsilon_{i,t}$$

regressions of financial flows on productivity from 1972 to 2019. We report panel regressions of financial flows on productivity from 1972 to 2019. We use the logarithm of total assets to measure firm size. Year and Firm fixed effects, and Frank and Goyal (2009) factors control variables are included in all regressions. Standard errors were clustered at firm level. Productivity is measured using dynamic panel regressions from regressing sales on three factors separately for each FF48 industries at each decade.

	(1) External Finance	(2) Net Debt Issue	(3) Net Equity Issue
Productivity	-0.070***	-0.025***	-0.040***
	(-14.4)	(-10.8)	(-12.3)
Productivity*Log(Assets)	0.007***	0.003***	0.004***
	(10.8)	(8.7)	(9.4)
Log(Assets)	0.507***	0.197***	0.272***
	(78.8)	(55.5)	(53.3)
Obs.	153969	153969	153969
Firm, Year FE	yes	yes	yes
Control Vars	yes	yes	yes
Adj R^2	0.620	0.256	0.519

Table 4: Small vs. Large Firms: Productivity Shocks and External Financing

This table examines how productivity affects financing decisions across firm size groups. Firms are sorted annually into quintiles based on total assets. All specifications include firm and year fixed effects, and control for the standard determinants of financing from Frank and Goyal (2009). Standard errors are clustered at the firm level and t-statistics are reported in parentheses. The sample period is 1972-2019. Panel A examines total external financing, Panel B focuses on net debt issuance, and Panel C examines net equity issuance. The average and median total assets for firms in each size quintile are reported in millions of dollars. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.

(a) Panel A: Total External Financing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	External Finance					
Productivity	-0.001	-0.021***	-0.014***	-0.006***	-0.001	0.003***
	(-0.8)	(-7.9)	(-5.7)	(-2.9)	(-0.4)	(3.1)
		Split into 5 groups				
Firm Size	All	Small	2	3	4	High
Average Size	2137	20	79	230	686	8756
Median Size	192	14	55	139	418	2895
Obs.	153969	26503	29611	31315	32681	33859
Adj R^2	0.248	0.379	0.390	0.341	0.252	0.101

(b) Panel B: Net Debt Issuance

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Net Debt Issue					
Productivity	0.001***	-0.004***	-0.000	0.000	0.000	0.002***
	(2.9)	(-3.0)	(-0.4)	(0.3)	(0.1)	(2.9)
		Split into 5 groups				
Firm Size	All	Small	2	3	4	High
Obs.	153969	26503	29611	31315	32681	33859
Adj R^2	0.028	0.052	0.093	0.116	0.126	0.066

(c) Panel C: Net Equity Issuance

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Net Equity Issue					
Productivity	-0.002***	-0.014***	-0.013***	-0.006***	-0.000	0.001***
	(-3.2)	(-6.1)	(-5.8)	(-3.6)	(-0.3)	(2.8)
		Split into 5 groups				
Firm Size	All	Small	2	3	4	High
Obs.	153969	26503	29611	31315	32681	33859
Adj R^2	0.288	0.364	0.347	0.279	0.196	0.116

Table 5: Small vs. Large Firms: External Financing and Investment

This table examines how external financing affects investment decisions across firm size groups. Firms are sorted annually into quintiles based on total assets. All specifications include firm and year fixed effects, and control for the standard determinants of financing from Frank and Goyal (2009). Standard errors are clustered at the firm level and t-statistics are reported in parentheses. The sample period is 1972-2019. In Panel A, we regress investment, measured as capital expenditure, on external finance. In Panel B, we regress investment on the fitted value of external finance. The fitted value of external finance is calculated using the coefficients estimated from regressing external finance on productivity, as shown in Table A.4. The average and median total assets for firms in each size quintile are reported in millions of dollars. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.

(a) Panel A

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Investment					
External Finance	0.077***	0.067***	0.073***	0.077***	0.089***	0.088***
	(6.7)	(6.9)	(6.6)	(7.1)	(6.8)	(5.9)
		Split into 5 groups				
Firm Size	All	Small	2	3	4	High
Average Size	2137	20	79	230	686	8756
Median Size	192	14	55	139	418	2895
Obs.	153969	26503	29611	31315	32681	33859
Adj R^2	0.328	0.201	0.315	0.369	0.428	0.408

(b) Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Investment					
Fitted External Finance	0.097***	0.073***	0.071***	0.110***	0.116***	0.124***
	(10.7)	(8.5)	(7.9)	(10.9)	(10.7)	(10.6)
		Split into 5 groups				
Firm Size	All	Small	2	3	4	High
Obs.	153969	26503	29611	31315	32681	33859
Adj R^2	0.310	0.188	0.297	0.357	0.410	0.393

Table 6: Causal Identification Using State R&D Tax Credits

The table reports panel regressions of financial flows on productivity from 1990 to 2006. In Panel A, We report a linear regression model

$$Prod \times R\&DCost = \beta_0 + ... + \beta_P Prod + \beta_{PS} Prod \times TaxCredit + \epsilon$$

$$PR\&DCost = \beta_0 + ... + \beta_T TaxCredit + \epsilon$$

Where the dependent variable is the interaction between productivity and the user cost of R&D, and the the user cost of R&D, respectively. The independent variable is our instrumental variable, which is the interaction between productivity and state-year-specific tax credits in the state of the firm's headquarters, and state-year-specific tax credits. In Panel B, we provide estimates of the heterogeneous relationship between firm size and productivity on net financing.

$$y = \beta_0 + ... + \beta_P Prod + \beta_{PS} Prod \times R\&DCost + \epsilon$$

Columns (1) to (3) report results for the uninstrumented panel regression, while Columns (4) to (6) report results using the instrumented approach. The user cost of R&D is from Bloom, Schankerman and Van Reenen (2013). Year and firm fixed effects, as well as Frank and Goyal (2009) factors, are included as control variables in all regressions. Standard errors are clustered at the firm level. In Panel C, we examine how productivity affects financing decisions across firm size groups for firms with high and low user costs of R&D. Firms are sorted annually into quintiles based on total assets. Large firms and small firms are those that belong to the top and bottom quintile groups, respectively. Firms are also sorted annually into quintiles based on the user cost of R&D, which is the predicted user cost of R&D from the first-stage regression. High R&D cost firms and low R&D cost firms are those that belong to the top and bottom quintile groups, respectively. We then regress external financing on productivity for these groups. All specifications control for the standard determinants of financing from Frank and Goyal (2009). T-statistics are reported in parentheses.

(a) Panel A. First Stage Regressions

	Productivity*R&D Cost	R&D Cost
Productivity*Tax Credit	-0.799***	
	(-11.6)	
Productivity	-0.085***	
	(-10.1)	
Tax Credit		-0.492***
		(-11.0)
Obs.	28036	28036
Firm, Year FE	yes	yes
Control Vars	yes	yes
Adj R^2	0.865	0.869
Wald F statistic:	338.101	
Anderson-Rubin Wald test P-val	0.000	

(b) Panel B: Productivity Interaction

	(1) External Finance	(2) Net Debt Issue	(3) Net Equity Issue	(4) External Finance	(5) Net Debt Issue	(6) Net Equity Issue
Productivity*R&D Cost	-0.017**	-0.009*	-0.006			
	(-2.0)	(-1.7)	(-1.1)			
Fitted Productivity*R&D				-0.135**	-0.054**	-0.064
				(-2.5)	(-2.2)	(-1.4)
Productivity	-0.008**	-0.002	-0.005*	-0.023***	-0.008**	-0.013**
	(-2.0)	(-1.3)	(-1.7)	(-3.2)	(-2.4)	(-2.2)
Obs.	28036	28036	28036	28036	28036	28036
Firm, Year FE	yes	yes	yes	yes	yes	yes
Control Vars	yes	yes	yes	yes	yes	yes
Adj R^2	0.441	0.092	0.434	0.230	0.016	0.219

(c) Panel C: Sorting by R&D Cost

	High R&D Cost		Low R&D Cost	
	(1) Small Firms	(2) Large Firms	(3) Small Firms	(4) Large Firms
Productivity	-0.023***	0.005	0.373	0.012*
	(-4.2)	(1.8)	(1.1)	(1.9)
Controls	Yes	Yes	Yes	Yes
Obs.	8528	8009	580	785
Adj R^2	0.450	0.147	0.691	0.052

Table 7: Causal Identification Placebo Test

The table reports panel regressions of financial flows on productivity from 1990 to 2006. In Panel A, We report a linear regression model

$$Prod \times R\&DCost = \beta_0 + ... + \beta_P Prod + \beta_{PS} Prod \times PseudoTaxCredit + \epsilon$$

$$PR\&DCost = \beta_0 + ... + \beta_T TaxCredit + \epsilon$$

Where the dependent variable is the interaction between productivity and the user cost of R&D, and the the user cost of R&D, respectively. The independent variable is 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. In Panel B, we provide estimates of the heterogeneous relationship between firm size and productivity on net financing.

$$y = \beta_0 + ... + \beta_P Prod + \beta_{PS} Prod \times R\&DCost + \epsilon$$

The pseudo user cost of R&D is derived from Bloom, Schankerman and Van Reenen (2013), but the starting date of the tax credits is randomly altered. Year and firm fixed effects, as well as Frank and Goyal (2009) factors, are included as control variables in all regressions. Standard errors are clustered at the firm level. In Panel C, we examine how productivity affects financing decisions across firm size groups for firms with high and low user costs of R&D. Firms are sorted annually into quintiles based on total assets. Large firms and small firms are those that belong to the top and bottom quintile groups, respectively. Firms are also sorted annually into quintiles based on the pseudo user cost of R&D, which is the predicted user cost of R&D from the first-stage regression. High R&D cost firms and low R&D cost firms are those that belong to the top and bottom quintile groups, respectively. We then regress external financing on productivity for these groups. All specifications control for the standard determinants of financing from Frank and Goyal (2009). T-statistics are reported in parentheses.

(a) First Stage

	Productivity*R&D Cost	R&D Cost
Productivity*Pseudo Tax Credit	-0.100	
	(-1.0)	
Productivity	-0.128***	
	(-18.4)	
Pseudo Tax Credit		-0.010
		(-0.2)
Obs.	27375	28036
Firm, Year FE	yes	yes
Control Vars	yes	yes
Adj R^2	0.859	0.894

(b) Productivity Interaction

	(1) External Finance	(2) Net Debt Issue	(3) Net Equity Issue
Fitted Productivity*Pseudo R&D	-0.393	-0.089	-0.219
	(-1.1)	(-0.6)	(-0.8)
Productivity	-0.055	-0.012	-0.033
	(-1.2)	(-0.7)	(-0.9)
Obs.	27375	27375	27375
Firm, Year FE	yes	yes	yes
Control Vars	yes	yes	yes
Adj R^2	0.206	0.012	0.210

(c) Sorting by R&D Cost

	High Pseudo R&D Cost		Low Pseudo R&D Cost	
	(1) Small Firms	(2) Large Firms	(3) Small Firms	(4) Large Firms
Productivity	-0.024***	0.005	0.351	0.008
	(-4.2)	(1.6)	(1.0)	(1.1)
Controls	Yes	Yes	Yes	Yes
Obs.	8449	7762	700	937
Adj R^2	0.449	0.150	0.652	0.040

Table 8: Parameter Estimation For Counterfactuals

The table reports the estimation of key parameters, including the 25th percentile, median, and 75th percentile. To estimate demand elasticity σ, we run the following regression for each industry in each decade:

$$\ln\left(\frac{p_i y_i}{p_j y_j}\right) = \kappa_0 + \kappa_1 \ln\left(\frac{a_i}{a_j}\right)$$

where we fix j as the firm with the largest sales revenue within industry and run the regression for each industry. σ is calculated using the following formula: $\sigma^* = \kappa_1^* + 1$, where κ_1^* is estimated coefficient from the regression. To estimate the fixed costs parameters ϕ, we run the following probit model for each industry in each decade:

$$\Pr(NotUpgrade_i = 1) = \Phi(\beta_0 + \beta_1 p_i y_i)$$

where $NotUpgrade_i = 1$ if firms belongs to the smallest two quintiles size group and $p_i y_i$ are firms sales revenue. ϕ is calculated using the following formula: $\phi = -\frac{\beta_0^*}{\beta_1^*}(\frac{\sigma-1}{\sigma})^{2-\sigma}\frac{1}{1+r}$, where β_0 and β_1 are estimated coefficients from the regression, and $r = 0.082$ which is calculated by taking the firm's total interest payments and dividing them by the firm's total debt. We also report $\frac{\phi}{AT}$, which is computed as the ratio of estimated ϕ and firms' total assets. In Panel (b), we present the median values for eight different industries.

(a) Estimates

	Median	p25	p75	Standard Error
σ	1.132	1.027	1.992	1.046
ϕ	71.413	8.643	209.407	1148.048
$\frac{\phi}{AT}$	0.318	0.041	1.893	76.231

(b) Industry-specific estimates

	Business Services	Retail	Electronic Equipment	Petroleum and Natural Gas
σ	1.030	2.000	1.035	1.029
ϕ	5.963	188.487	17.105	8.712
$\frac{\phi}{AT}$	0.049	0.734	0.146	0.031
	Pharmaceutical Products	**Wholesale**	**Machinery**	**Computers**
σ	1.007	1.638	3.702	1.050
ϕ	3.349	185.375	299.332	6.859
$\frac{\phi}{AT}$	0.031	1.245	2.390	0.102

A Appendix: Variable Definitions

Our empirical work requires variables that measure firm productivity, financing decisions, and firm characteristics. The construction of these variables follows established approaches in the corporate finance literature (Mitton, 2022; Frank and Goyal, 2024) together with additional controls that are more specific to our problem.

Productivity is critical to our analysis. We estimate firm-level productivity using a production function approach that is based on standard corporate accounting. Our baseline specification models the logarithm of sales as a function of cost of goods sold (COGS), selling, general and administrative expenses (SGA), and total assets (AT).

$$\ln(Sales_{it}) = \alpha_C \ln(COGS_{it}) + \alpha_S \ln(SGA_{it}) + \alpha_{AT} \ln(Assets_{it}) + \omega_{it} + \epsilon_{it} \tag{5}$$

The residual term ω_{it} represents our measure of productivity. It is the firm's ability to generate sales beyond what would be predicted by its observed inputs. We estimate this specification separately for each Fama-French 48 industry in each decade. This approach permits technological differences across sectors and potential changes in production relationships over our sample period. Our estimation employs both standard OLS and dynamic panel techniques following Blundell and Bond (1998) to address potential simultaneity between productivity and input choices.

We construct standard measures of external financing as in Frank and Goyal (2009); Mitton (2022). Our primary measure, external finance, is the total net inflow of external capital. It is defined as the sum of net debt issuance and net equity issuance, scaled by lagged total assets. This scaling ensures comparability across firms of different sizes and is standard in the capital structure literature.

Net debt issuance is calculated as long-term debt issuance (Compustat item DLTIS) minus long-term debt reduction (DLTR) plus changes in current debt (DLCCH), all scaled by lagged total assets. For firms without reported debt issuance or reduction data, we calculate this variable using balance sheet changes in debt obligations. Net equity issuance is measured as the sale of common and preferred stock (SSTK) minus the purchase of common and preferred stock (PRSTKC), scaled by lagged total assets. This is the equity raised from public offerings and private placements, net of share repurchases.

We measure firm size using total assets converted to 2019 dollars using the GDP deflator from the Federal Reserve Economic Data (FRED) database. Our main measure of firm size is a sort of firms into quintiles in the specific year. We use this to examine how productivity-financing relationships vary across the firm size distribution while controlling for time trends.

Our regressions include a standard set of control variables known to affect financing decisions, following Frank and Goyal (2009). The market-to-book ratio is calculated as the market value of assets divided by book assets. It is often interpreted as reflecting growth opportunities. The market value of assets is defined to be the book value of assets plus the market value of equity minus the book value of equity. Asset tangibility is measured as net property, plant, and equipment (PPENT) divided by total assets. This is commonly interpreted as a measure of potential collateral value. Profitability is defined as operating income before depreciation (OIBDP) divided by total assets. This is a measure of internal cash flow generation. We include the median industry leverage ratio defined by Fama-French 48 industry classifications each year. When using size as a control variable we measure it as the natural logarithm of inflation-adjusted sales. For investment analysis, capital expenditure is measured as capital expenditures (CAPX) scaled by lagged property, plant and equipment. This is interpreted as the rate of tangible capital formation.

For the instrumental variables approach, we use data on state-level R&D tax credits from Wilson (2009), updated through 2020. The user cost of R&D capital incorporates both federal and state-level tax incentives for R&D investment, following the methodology in Bloom, Schankerman and Van Reenen (2013).

All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the impact of extreme observations. Financial firms (SIC codes 6000-6999) and regulated utilities (SIC codes 4900-4949) are excluded from our analysis due to their distinct regulatory environments and financing patterns.

Table A.1: Data Cleaning Steps

Step	Description	Observations
Start	COMPUSTAT/CRSP Fundamentals Annual Merged 1950 to 2019	326,248
Drop	fyear<1970 | fyear>2020 | fyear missing	-19,192
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 capital, labor, investment, COGS, XSGA	-21,223
Drop	Missing Equity and Debt Issuance and Repurchase	-5,245
Final Sample		153,969

Table A.2: Summary Statistics by Firm Size Quintile

This table presents the sample means of several key variables from 1970 to 2019 for each size quintiles. The mean value for each variable is reported.

	(1)	(2)	(3)	(4)	(5)
Size	Small	2	3	4	Large
Productivity	0.95	1.32	1.48	1.64	2.12
External Finance	0.15	0.09	0.07	0.06	0.04
Net Debt Issue	0.02	0.02	0.03	0.04	0.03
Debt Issue	0.09	0.10	0.13	0.14	0.13
Debt Repurchase	0.06	0.08	0.10	0.10	0.09
Net Equity Issue	0.12	0.07	0.04	0.02	0.00
Equity Issue	0.13	0.08	0.06	0.04	0.02
Equity Repurchase	0.01	0.01	0.01	0.01	0.02
Investment Rate	0.06	0.06	0.07	0.07	0.07
Asset Growth	0.05	0.03	0.05	0.05	0.04
Cash	0.24	0.20	0.16	0.12	0.09
Sales	24.78	97.84	284.02	812.09	6273.49
Total Assets	20.31	79.46	229.51	686.48	8756.14
Observations	26503	29611	31315	32681	33859

Table A.3: Production Function Estimation By Decade the Averaged

This table presents results of production function estimation for the training sample of firms from 1972 to 2019. Production function is in standard Cobb Douglas form. Output is measured as sales. The input variables are COGS, SGA, and total assets. Capital is measured using gross property, plant, and equipment (PPEGT) deflated by price deflator for investment following İmrohoroğlu and Tüzel (2014). Labor is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration. The models are estimated using OLS and dynamic panel regression separately for each Fama-French 48 industries in each decade. The average coefficients and standard deviation of coefficients are reported. Column (2) represent OLS regression of all variables in first differences, column (3) adds input level as additional control variables. Column (4) presents the results of a dynamic panel regression, regressing sales on input levels and lagged sales. We estimate the equation using system GMM (Blundell and Bond, 1998). A few observations are lost due to variables lagging at the beginning of the sample.

	(1) OLS	(2) OLS First Diff	(3) OLS First Diff	(4) Dynamic Panel
COGS	0.718		-0.002	0.497
	(0.018)		(0.005)	(0.073)
SGA	0.181		0.000	0.108
	(0.015)		(0.008)	(0.037)
Total Assets	0.162		-0.001	0.135
	(0.0120)		(0.015)	(0.048)
Δ COGS		0.718	0.717	
		(0.043)	(0.012)	
Δ SGA		0.179	0.179	
		(0.039)	(0.016)	
Δ Total Assets		0.116	0.117	
		(0.033)	(0.014)	
L.Output				0.305
				(0.072)
Obs.	153969	153969	153969	153969
Adj R^2	0.973	0.772	0.774	

Table A.4: Panel Estimates of Productivity Effects

This table performs examine the relationship between financial flows and productivity. Productivity is measured using dynamic panel regressions from regressing sales on three factors separately for each FF48 industries at each deacade. Three factors include COGS, SGA and total assets. Frank and Goyal (2009) factors were included. We report panel regressions of financial flows on productivity from 1972 to 2019. Year and Firm fixed effects, and control variables are included in all regressions. Observations were further divided into different sample period. Standard errors were clustered at firm level.

Dependent variable:	(1) External Finance	(2) Net Debt Issue	(3) Net Equity Issue
Productivity	-0.001	0.001***	-0.002***
	(-0.8)	(2.9)	(-3.2)
Control Vars	yes	yes	yes
Firm, Year FE	yes	yes	yes
Sample Period	1971-2019	1971-2020	1971-2023
Obs.	153969	153969	153969
Adj R^2	0.248	0.028	0.288
Productivity	-0.001	0.001	-0.002*
	(-0.5)	(1.6)	(-1.7)
Control Vars	yes	yes	yes
Firm, Year FE	yes	yes	yes
Sample Period	1971-1999	1971-2000	1971-2003
Obs.	95564	95564	95564
Adj R^2	0.173	0.024	0.206
Productivity	-0.001	0.002***	-0.003***
	(-0.8)	(3.3)	(-3.8)
Control Vars	yes	yes	yes
Firm, Year FE	yes	yes	yes
Sample Period	2000-2019	2000-2020	2000-2023
Obs.	58405	58405	58405
Adj R^2	0.357	0.033	0.407