Is R&D Rivalry Slowing the Growth of Productive Firms?

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Abstract: Productive firms tend to grow their employment faster, enhancing aggregate productivity through reallocation. However, job reallocation rates have declined substantially in recent decades, contributing to slower productivity growth. This paper explores the hypothesis that technological rivalry slows productive firm growth. Using microdata from the US Census, we find that technological rivalry has been rising and is associated with slower growth of productive firms. Estimating counterfactual firm growth from 1997-2018, technological rivalry accounts for most of the decline in job reallocation. Facing rising technological rivalry, firms respond more slowly or not at all to productivity-raising innovations, dampening aggregate productivity growth.

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1. Introduction

Economists generally view competition as a spur to innovation and productivity growth (for an overview see Gilbert 2006). However, from the perspective of individual firms seeking to maximize returns on innovation, technological rivalry poses a problem: other firms may develop technologies that reduce the future value of the innovator's own technology—these rivals create a risk of obsolescence. This risk affects the behavior and performance of innovating firms. Prior research finds that technological rivalry can reduce innovation incentives (Mezzanotti and Simcoe 2023b; Ando et al. 2025; Bessen and Wang 2024). By the same logic, obsolescence risk might affect the *implementation* of new technology by shortening the time horizons firms use when deciding whether to adopt an innovation, diffuse it, or expand production of it.. For instance, a firm, having realized a productive innovation, may choose to grow more slowly in the face of obsolescence risk and adoption costs.

This paper explores how technological rivalry affects the growth rate of productive firms in the US in recent decades. This is an important topic not only for individual innovators, but also for aggregate productivity growth. Firm growth hastens the reallocation of resources to more productive firms, providing an important component of aggregate growth. (Foster et al. 2001, 2008, 2016; Baqaee and Farhi 2020). Unfortunately, the pace of this reallocation has slowed in recent decades (Hyatt and Spletzer 2013; Davis and Haltiwanger 2014; Decker et al. 2020; Biondi et al. 2025). Decker et al., using a very general framework, find that the decline in job reallocation can be attributed to a declining response to productivity shocks, e.g., firms receiving positive productivity shocks do not grow as fast

as they would have in the past. They suggest that labor adjustment costs may have risen, decreasing firm responsiveness (see also Cooper et al. 2024).[1]

We propose another, possibly complementary, factor: rising technological rivalry and obsolescence risk. A variety of adjustment cost/investment models involve balancing irreversible investments such as hiring costs against uncertain future revenues enabled by those investments (Pindyck 1988; Dixit 1989; Bentolila and Bertola 1990; Hopenhayn and Rogerson 1993). These models can explain why firms frequently choose not to invest (see e.g. Davis and Haltiwanger 1992), even after a positive productivity shock. But obsolescence risk affects this tradeoff because it affects the expected present value of future revenues. We develop a model of technology adoption with adjustment costs and show that a firm facing higher obsolescence risk may respond more slowly to positive productivity shocks or may be less likely to respond at all.

Building on prior work (Ando et al. 2025), we use this model to estimate a measure of technological rivalry. This measure has been rising robustly over the last several decades and it relates to firm growth. We find that firms facing greater rivalry are likely to grow more slowly, and they are more likely to choose inaction, that is, to neither increase nor decrease employment significantly. This behavior slows the average response to productivity shocks. We find that rising technological rivalry accounts for mean declines in firm growth from 4 to 15 percent. Applying our estimates to the US non-farm business sector, we find that most of the decline in job reallocation since 1997 is accounted for by technological rivalry.

[1] Biondi et al. (2025) find a similar decline in job reallocation rates in Europe, but they suggest that labor adjustment costs do not account for the decline there.

Obsolescence and Technological rivalry

A rise in technological rivalry over the last decades might not seem too surprising given that R&D has more than doubled relative to GDP and that the effectiveness of R&D appears to have risen (Ando et al. 2025; Fort et al. 2025). Some indirect casual evidence provides further support in some industries. When Intel was threatened by rivals' products in the 1990s, it increased the pace of its own product introductions, shortening product life cycles. Shorter product lives imply higher obsolescence. A similar pattern is seen in semiconductors and electronic components industries generally where product lives have been reduced by 60 percent (Aizcorbe 2005; Hochbaum et al. 2011 Figure 1; Mariani 2024; Ackerman 2025). Rivalry in the form of product proliferation is observed in many markets, including automobiles, breakfast cereals, and sports shoes (Aichner and Coletti 2013), and can be inferred from the seven-fold growth in new trademark registrations since 1980 (data source: USPTO), a rough proxy for the overall number of new products in the economy.

To obtain econometric estimates of technological rivalry, we use a method developed in a previous paper for use in the US manufacturing sector (Ando et al. 2025). Here, we do the estimation for the entire non-farm business sector from 1976 to 2018. Our estimation is based on the idea that rivals' R&D raises firm obsolescence risk, reducing expected returns, thus leading firms to reduce their R&D, all else equal. We develop an R&D demand function where we regress firm R&D against rivals' past R&D plus other controls. We find rivals' R&D is strongly associated with lower R&D investment by the focal firm. Moreover, instrumental variable analysis suggests that this association is plausibly causal.

We calculate the mean impact of rivals' R&D on focal firm R&D as a measure of technological rivalry, we find that this measure has increased substantially over time, beginning around the Dotcom boom, and this finding is robust to a variety of possible

confounding factors such as industry competition conditions and markups. This measure of technological rivalry also corresponds to common notions of business dynamism. For example, industries with higher technological rivalry tend to have higher exit and entry rates, more rapid turnover of market leaders, younger firms, and lower industry concentration. The software and biotech industries score high on our measure of technological rivalry. Thus, both our econometric estimates and casual evidence support the hypothesis of rising technological rivalry.

Several other papers have derived obsolescence rates for R&D (Mead and others 2007; Huang and Diewert 2011; Li and Hall 2020). Our approach differs because we explicitly consider the effect of technological rivalry on obsolescence rates, allowing obsolescence rates to vary across firms, within industries, and over time.

Several papers find that increased product market competition resulting from deregulation or increased competition from foreign firms is linked to greater reallocation (Olley and Pakes 1996; Sivadasan 2009; Arnold et al. 2011; Alfaro and Chari 2014; Xu and Gong 2017; Alfaro and Chen 2018), although Backus (2020) finds competition is not related to productive reallocation in one industry study. We study technological rivalry, which is quite distinct from competition arising from lower regulatory or trade barriers. We find that technological rivalry can slow reallocation.

In two related papers, we explore how rivalry affects the contribution of R&D to productivity growth and the unequal distribution of R&D across firms (Bessen and Wang 2024; Ando et al. 2025). Some portion of this text overlaps with those papers.

We next describe our model that provides us with regression specifications for estimating technological rivalry and the impact of rivalry on firm growth. Then we describe our data and present our empirical findings.

2. Model: Firm growth with obsolescence

Employment growth

We start with a setting where the focal firm adopts a new technology, although the firm does not necessarily develop that technology itself. They could license the technology or copy it, or it could be shared or Open Sourced. In our data, only 3 percent of firms invest in R&D, although these firms account for 38 percent of firm revenue (Bessen and Wang 2024). Below we will consider the instance where the firm does invest in R&D, and we use observed R&D behavior to infer our measure of technological rivalry.

Assume that the new technology constitutes a new product line with revenue R_t at time *t*. Without loss of significant generality, we treat each firm as having a single product line. Following Decker et al. (2020), let $R(A_t, E_t) = A_t E_t^{\phi},\ \phi < 1$, where employment, E_t, is the sole input and A_t is revenue productivity. The exponent ϕ is less than 1 to capture markups or decreasing returns to scale.

The firm's productivity is initially determined by the adoption of the new technology in period 1, $A_1 = \overline{A}$. But after the first period, productivity is subject to exogenous shocks ν drawn from a stationary distribution such that $\ln A_{t+1} = \ln A_t + \nu, \quad \mathbb{E}[\nu] = 0, \mathrm{var}[\nu] = \sigma^2$. There are two other ways that technology affects the firm. We assume a technology adoption cost, T, which may be thought of as a sunk training cost per each new employee hired. This training cost is specific to the new technology, so workers trained on other technologies/product lines need to be retrained when hired here. Prior to adoption and training, the product line has no employees, $E_0 = 0$, This setup is similar to models with linear piecewise adjustment costs, although we ignore firing costs (Bentolila and Bertola 1990; Hopenhayn and Rogerson 1993). This simple version suffices for our exposition.

Also, the technology makes firm profits subject to obsolescence. Given wage W the flow of profits at year *t* is

$$\pi_t = R(A_t, E_t) - WE_t - T \cdot \max(0, E_t - E_{t-1}).$$

This stream of profits is subject to obsolescence, meaning that external developments can reduce the value of the profit stream with some probability. This can happen if a rival product replaces the firm's product or reduces its profit in a differentiated market, or if industry standards change, or if market demand changes, etc. Given discount rate r and obsolescence rate δ, the Bellman equation for the value of the profit stream is

$$V(E_{t-1}) = \max_{E_t}[R(A_t, E_t) - WE_t - T \cdot \max(0, E_t - E_{t-1}) + B \cdot \mathbb{E}[V(E_t)]] \qquad (1)$$

where B is a discount factor, $B \equiv \frac{1-\delta}{1+r} < 1$.

In year *t*, the firm can take three courses of action:

1. With probability P_1 the firm chooses $E_t < E_{t-1}$, in which case the flow of profits is $R(A_t, E_t) - WE_t$.
2. With probability P_2 the firm chooses $E_t = E_{t-1}$, in which case the flow of profits is $R(A_t, E_{t-1}) - WE_{t-1}$.
3. With probability P_3 the firm chooses $E_t > E_{t-1}$, in which case the flow of profits is $R(A_t, E_t) - WE_t - T(E_t - E_{t-1})$.

The same choices apply in subsequent years, and we can show that because ν is drawn from a stationary distribution, the probabilities P_j remain constant. The solution is derived in the Appendix and shown in Figure 1, which uses lower case variables to designate logs, $e = \log E$, $a = \log A$. The zone boundaries are

$$a^1 = (1-\phi)e_{t-1} + \ln\left(\frac{1}{\phi}\left(W - TBP_3(1-BP_2)\right)\right) \qquad (2)$$
$$a^3 = (1-\phi)e_{t-1} + \ln\left(\frac{1}{\phi}\left(W + T(1-BP_3)(1-BP_2)\right)\right)$$

and the employment in zones 1 and 3 is, respectively,

$$e^1 = \frac{1}{1-\phi}\left(a_t + \ln\left(\frac{\phi}{W - TBP_3(1-BP_2)}\right)\right), \tag{3}$$
$$e^3 = \frac{1}{1-\phi}\left(a_t + \ln\left(\frac{\phi}{W + T(1-BP_3)(1-BP_2)}\right)\right).$$

The solution is then

$$e_t^* = \begin{Bmatrix} e^1, & a_t < a^1 & I \\ e_{t-1}, & a^1 \leq a_t \leq a^3 & II \\ e^3, & a^3 > a_t & III \end{Bmatrix}. \tag{4}$$

At low draws of a_t, the firm reduces employment from the previous period. As a_t increases, the employment level increases until the boundary a^1 is reached. At this point, the firm leaves employment unchanged. This zone of inaction holds until a_t reaches boundary a^3, at which point employment begins to rise again. Note that the slope of the relationship is the same in zones 1 and 3, $\frac{\partial e^1}{\partial a_t} = \frac{\partial e^3}{\partial a_t} = \frac{1}{1-\phi}$.

Following Decker et al. (2020), we can obtain an equation for forward employment growth by taking the difference between years $t+1$ and t. Taking the solution zone in period $t+1$, sweeping wages and constants into fixed effects, *FE*, and allowing for a lower intercept for e^3

$$e_{t+1} - e_t = \Delta e_t \approx \begin{Bmatrix} \frac{1}{1-\phi} a_{t+1} + FE - e_{t,} & I \\ 0, & II \\ \frac{1}{1-\phi} a_{t+1} + FE - const - e_t, & III \end{Bmatrix}. \tag{5}$$

In our data we observe firms in all three zones depending on their draws of ν_t. Using these data to regress employment growth on productivity, the average relationship will depend on the frequency with which shocks ν fall in each zone. Then an average relationship might be written

$$\Delta e_t \approx \frac{(1-P_2)}{1-\phi} a_{t+1} - P_3 C + FE - e_t(1-P_2).$$

The first coefficient represents the responsiveness of firm growth to productivity. As this term shows, productivity increases employment growth in zones I and III but not in zone II, the inaction zone. Importantly, examining the expression for the productivity boundaries in (3), it is straightforward to show that $\frac{d\,(a^3-a^1)}{d\,\delta} > 0$. That is, the size of the inaction zone increases with the obsolescence rate. We test this in the data below.

We can write a version of this relationship to estimate:

$$\Delta e_{it} = \theta_a a_{it+1} + \theta_x a_{it+1} \cdot \delta_{it} + \theta_\delta \delta_{it} - e_{it} + \theta_e e_{it} \delta_{it} + \mu_{jt} + \epsilon_{it}. \qquad (6)$$

We expect that $\theta_a > 0,\ \theta_x, \theta_\delta < 0$. Below we supply a flexible functional form to replace δ. This equation illustrates that obsolescence can reduce the growth response to productivity and that obsolescence might also directly tend to reduce firm growth rates. While this result was obtained with a specific type of adjustment cost function (training or adoption cost), the effect of obsolescence on firm growth might well be expected with a variety of adjustment cost models that trade current cost for future expected revenue.

R&D Demand

We measure endogenous obsolescence risk by estimating how R&D-performing firms reduce their own R&D in response to rivals' R&D. Our general model of firm employment growth can be applied to the specific case where firms invest in R&D to create their own innovations. Following the R&D literature, we assume that the firm invests I in R&D, and this investment produces a product innovation with initial productivity $A_1 = I^\beta,\ \ \beta < 1$, where, as before $\ln A_{t+1} = \ln A_t + \nu$ and $\mathbb{E}[\nu] = 0$ is an exogenous random shock. The rest of the setup is the same as before. Letting the price of R&D be p_I, the Bellman equation for this firm is now

$$V(E_{t-1}) = \max_{E_t, I}[R(A_t, E_t) - WE_t - T \cdot \max(0, E_t - E_{t-1}) + B \cdot \mathbb{E}[V(E_t, I)] - p_I I]\,. \quad (7)$$

Expressing this as an infinite sequence,

$$V(E_{t-1}) = \max_{E_t, I}\left[\begin{array}{c} R(A_t, E_t) - WE_t - T \cdot \max(0, E_t - E_{t-1}) - p_I I \\ + \sum_{\tau=1}^{\infty} B^{\tau}(\mathbb{E}[R(A_t, E_t) - WE_t - T \cdot \max(0, E_t - E_{t-1})])\end{array}\right].$$

As above, $\mathbb{E}[A_{t+n}] \approx A_1 = I^{\beta}$ and $\mathbb{E}[R_{t+n}] \approx R_1 = I^{\beta} E_t^{\phi}$. Using this and taking the first partial derivative with respect to *I*, the first order condition for R&D is

$$\frac{\beta R_t / I}{1 - B} - p_I = 0.$$

Rearranging and taking logs, we get an R&D demand equation,

$$\ln \hat{I} = \ln R - \ln(r + \delta) + \ln\left(\frac{\beta(1 + r)}{p_I}\right) + \epsilon \quad (8)$$

This model is for a single innovation. Firms, of course, have many product lines and many R&D projects at any one time, but the R&D demands for separate products can be aggregated. In a related paper (Ando et al. 2025), we develop an R&D demand equation for multi-product firms with an R&D capital stock that incorporates many R&D projects. That model produces an R&D demand equation that is essentially the same as equation (8).

Empirical implementation

To implement an estimation of this equation, we need a flexible functional form to capture $\ln(r + \delta)$. Our hypothesis is that the obsolescence rate δ increases with rivals' R&D, so we would like to include a variable that captures the sum of rivals' R&D, S^*. But who are the rivals? A firm's technology rivals are those firms that might potentially develop new knowledge that reduces the value of the focal firm's technology. Technology rivals are not necessarily product market competitors; they might be in an entirely different industry but work in a related technology space. Innovations from these rivals might allow them to

become product market competitors or might indirectly affect the focal firm's future profits. For example, the HTML5 web standard undermined Adobe's Flash product, but few of the firms developing the standard were Adobe competitors. This risk affects the focal firm's R&D investment.

As a proxy for S^*, we use the sum of other firms' R&D in the same primary industry as the focal firm, letting

$$\ln(r + \delta_{it}) = \ln r + \gamma \ln S_{it} + \varepsilon, \quad S_{it} \equiv \sum\nolimits_{\substack{j \neq i \\ j \in J}} I_{jt} \tag{9}$$

where J is the primary industry (6-digit NAICS) of firm i and ε is an error term. The variable S should be correlated with the true measure, S^*, so it provides a proxy albeit with measurement error.[2] The error term ε captures, among other things, the extent to which obsolescence risks arises from R&D performed outside the focal firm's industry.

The expression in equation (7) can be used to estimate equation (6). This procedure does, however, raise some econometric concerns. One is possible endogeneity: if firms in the same industry experience a common "technological opportunity" shock (captured in the variable A), the error term in the R&D demand equation, ϵ, will be correlated with S—both the focal firm and its rivals will have higher R&D with such a shock. That will tend to bias estimates of γ upwards. That is not too worrisome because we expect γ, the effect of rivals' R&D, to be negative, so our estimates will be understated. Nevertheless, to control for endogeneity we do two things: first, we use lagged versions of rivals' R&D, S_{it-1}; second, following a procedure developed by Bloom et al. (2013), we use an instrumental variable to

[2] In an earlier paper (Bessen and Wang 2024), we considered an alternative measures of rivals' R&D across multiple industries and found similar results.

obtain a predicted measure of rivals' R&D that should be independent of these common shocks. Described in the Appendix, the predicted measure is derived using the tax cost of R&D that varies over time and across states with changes in Federal and state R&D tax credits and depreciation allowances that are plausibly exogenous.[3] The Appendix describes this estimation in detail, it includes an alternative version that excludes rivals from the same state as the focal firm (these will have the same tax cost as the focal firm), and it also treats endogeneity of firm revenue.

Another concern is that this rivalry variable is constructed as a leave-one-out measure: for any year, S is the industry total minus the focal firm investment, and focal firm investment is the dependent variable, possibly allowing for spurious correlation. In the Appendix we estimate this bias and find that it is too small to materially affect our results.

Equation (7) also misses potential heterogeneity across firms because of switching costs. Larger or older firms might face lower obsolescence rates because their consumers may face higher costs of switching to a new product. Switching costs can arise for a variety of reasons including reputation (brand loyalty), complementary products, sunk investments in training or learning through use, network effects and more (Klemperer 1995). But higher switching costs means that consumers will leave more slowly when a rival introduces a superior product, making the obsolescence rate lower. To allow for this possibility, we add a term $\mu \ln R_{it} \ln S_{it}$ to (6) so that obsolescence rates may vary with firm revenue.

Finally, using inverse hyperbolic sine (asinh) because some industries have very small total R&D (and possibly poorly measured), and sweeping the price of R&D and the discount rate into the fixed effects, we get

[3] The tax cost data were developed by Barth et al. (2023) and graciously shared with us.

$$\ln I_{it} = \gamma_t + \gamma_J + \gamma_S \operatorname{asinh} S_{it-1} + \gamma_x \operatorname{asinh} S_{it-1} \cdot \ln R_{it} + \gamma_R \ln R_{it} + \epsilon_{it}, \quad (10)$$

where γ_t and γ_J denote the year and industry fixed effects. We estimate this equation below and subject it to a series of robustness checks. This equation is the firm's reaction function given the R&D of other firms.

Of course, other firms' R&D affects the focal firm through another channel: knowledge spillovers. As other firms (not necessarily rivals) develop new knowledge, spillovers can benefit the focal firm via the variable A in the production function equation. Bloom et al. (2013) use patent data to weight the R&D of other Compustat firms by their technical proximity to the focal firm, thus measuring potential spillover knowledge. However, since only 18 percent of R&D performing firms obtain patents (Mezzanotti and Simcoe 2023a), we cannot construct such a measure for our more representative sample. Instead, we implicitly include the effect of knowledge spillovers in the $\ln R$ term in equation (8).

With estimates of the parameters in equation (8), we can estimate the impact of rivals' R&D on focal firm R&D as a measure of technological rivalry,

$$X_{it} = -(\hat{\gamma}_S \ln S_{it-1} + \hat{\gamma}_x \ln S_{it-1} \cdot \ln R_{it}). \quad (11)$$

Below in Section 4.1 we estimate this measure of technological rivalry over time, showing that it has risen.

We can further use these estimates to analyze firm growth. Assuming these estimated coefficients apply in equation (4), we can rearrange to get

$$\hat{\delta}_{it} = r(e^{X_{it}} - 1) \approx rX_{it} \quad (12)$$

where we use the first two terms of a Taylor series expansion to get the approximation. Then, adding an error term ϵ_{it}, equation (4) can be reparametrized as

$$\Delta e_{it} = \theta_a a_{it+1} + \theta_x a_{it+1} \cdot X_{it} + \theta_\delta X_{it} - e_{it} + \theta_e e_{it} X_{it} + \mu_{jt} + \epsilon_{it}. \qquad (13)$$

We estimate this equation below, using multi-factor productivity for the manufacturing sector and revenue labor productivity for the non-farm business sector.

3. Data

Innovation investment

Following our previous paper (Ando et al. 2025), our primary data sources on business investment in innovation are surveys administered by the US Census Bureau, the Survey of Industrial Research and Development (SIRD), which spans from 1976 to 2007, and the Business R&D and Innovation Survey (BRDIS), which covers from 2008 to 2018 (renamed the Business Research and Development Survey in 2017). These are annual surveys, conducted jointly with the National Science Foundation's National Center for Science and Engineering Statistics, collecting responses of approximately 40,000 (fewer in the earlier years) for-profit, nonfarm businesses with five or more employees. In addition to the R&D data, sales, sample weights, and imputation flags for R&D are drawn from the SIRD and BRDIS datasets. We then link these datasets to the Longitudinal Business Database (LBD) via the SIRD-BRDIS Walkway developed by Cohen (2023). The LBD contains employment, firm age, and industry (NAICS code) of virtually all private employer businesses in the United States.

A concern in analyzing the data over an extended period is that the scope of the sample in the R&D survey has changed. From 1976 to 1991, the survey focused on large firms in manufacturing industries. After 1992, firms in several non-manufacturing industries and small firms were added. Since 2008, the BRDIS survey has substantially increased the scope of the sample frame. To conduct analysis with a consistent scope sample, we have constructed revised sample weights and use them in the empirical analysis. The sample is

reweighted so that the composition of the sample in every year from 1976 to 2018 is similar to that of the SIRD datasets from 1976 to 1991.[4] We also perform our analysis over different time periods, each roughly a decade in length, during which sampling was mostly consistent. These periods are 1976-91, 1992-1999, 2000-2007, and 2008-2018.

Establishment and firm growth rates

We follow Davis, Haltiwanger, and Schuh (1996) to construct a growth measure (henceforth, DHS) for establishments (or firms),

$$g_{it} = 2 * \frac{E_{it+1} - E_{it}}{E_{it+1} + E_{it}}.$$

where E_{it} is the employment at establishment (firm) *i* at year *t*. This measure has the advantage that it exists for both continuing business units and also for exiting units. The employment variable comes from the LBD. The LBD provides a consistent record of employment, measured each March, for firms in the entire non-farm business sector.

Productivity

Manufacturing TFP

For the manufacturing sector we estimate a multifactor (TFP) productivity measure for establishments using the quinquennial Census of Manufactures (CM) with data from the Annual Survey of Manufactures (ASM) for the intervening years, using census identifiers. The CM collects statistics from all establishments except for some very small ones, while the ASM is a survey of approximately 50,000 establishments. Both datasets provide information on production inputs and outputs, enabling the estimation of total factor productivity (TFP) at the establishment level. In particular, real output (deflated revenue), real capital stock

[4] See Ando, Bessen, and Wang (2025) for the detailed procedure.

(including equipment and structures), and real material costs (intermediate inputs) are used in our analysis. We also use total factor productivity estimates from the Collaborative Micro-productivity Project (CMP) jointly developed by the BLS and Census Bureau (Cunningham et al. 2023). Overall, the data contain over 670,000 establishment-year observations for the manufacturing sector from 1976 through 2018.

We construct the measure of establishment-level TFP as follows:

$$\log(TFP_{it}) = \log(\text{revenue}_{it}) - \beta_{\text{labor}}\log(\text{labor}_{it}) - \beta_{\text{capital}}\log(\text{capital}_{it}) - \beta_{\text{int}}\log(\text{int}_{it}).$$

The data on revenue and three production inputs at the establishment level are drawn from the ASM, CM, and LBD. The three coefficients in the production function (i.e., $\beta_{\text{labor}}, \beta_{\text{capital}}, \beta_{\text{int}}$) are estimated by the control function approach, pioneered by Olley and Pakes (1996). Since firms endogenously choose production inputs in response to productivity shocks, the OLS estimate of the production function may be biased. The structural approach exploits firm investments to proxy unobserved productivity and address the endogeneity problem. We adopt the approach developed by Levinsohn and Petrin (2003), in which firms are assumed to adjust their intermediate inputs after observing their productivity shock.[5] The estimation is implemented by the prodest Stata package. We specify labor as a free variable, capital as a state variable, and intermediate inputs as a proxy variable. Furthermore, we estimate the production function at each NAICS 3-digit industry, as the nature of production funcation may differ across industries See Appendix Table A11. Once we estimate the production function, the TFP measure is obtained as in the equation above.

[5] Their approach uses intermediate inputs to proxy unobserved productivity because capital investments are lumpy and can be zero in many observations. Ackerberg, Caves, and Frazer (2015) propose an alternative approach that overcomes the potential functional dependence problem in Olley and Pakes (1996) and Levinsohn and Petrin (2003). However, this estimation method encounters convergence problems and yields negative production elasticities in some industries, as reported by Gao and Kehrig (2017).

We also use these inputs to calculate markups using the Raval method (2023b; 2023a) for intermediates.

Labor Productivity

Because variables needed to construct multifactor productivity are not fully available outside of the manufacturing sector, we measure labor productivity as deflated revenue per employee for the non-farm business sector. The employment data and the revenue data come from the revenue-enhanced LBD (LBDrev). This dataset enhances the LBD with data on firm revenue, as reported on business income tax forms, from the IRS (Haltiwanger et al. 2019). This procedure matches revenue for about 80 percent of the firms. To create more fully representative estimates, we follow Haltiwanger et al. (2016) using inverse propensity weights.[6] We obtain over 60 million firm-year observations from 1997 to 2018.

4. Empirical Findings

Technological Rivalry

Table 1 shows R&D demand regressions for each of the four periods. The regression coefficients are used to construct a measure of technological rivalry. The regressions are weighted by our rebased sample weights and standard errors are clustered by detailed industry. The dependent variable is the log of real domestic R&D spending. We use the inverse hyperbolic sine (asinh) rather than the log of rivals' R&D because this variable can be very small for some industries. Panel A shows the simple regression with just the rivals' R&D term on the right-hand side; the coefficients are negative and roughly larger over

[6] They obtained the predicted probability that a firm would appear in the matched sample using logistic regressions based on firm characteristics (firm size, firm age, employment growth rate, industry, and a multiunit status indicator). The inverse of these probability predictions provides weights to make regression estimates more representative.

time. Panel B adds terms involving log real revenues to proxy for the size of the customer base. For 2008 and after, we use worldwide net sales from BRDIS. For earlier years, however, SIRD does not consistently report worldwide sales, so we use domestic net sales interacted with a dummy variable indicating whether the firm has foreign R&D spending, an indicator of foreign activities.[7] The bottom row of the table reports estimates of the technological rivalry measure using equation (8).

The coefficients of rivals' investment, shown in the first row, are negative, meaning that rival firms' R&D in the last period is negatively associated with focal firms' R&D. Moreover, the implied effect of technological rivalry is quite large—at the sample means, technological rivalry is associated with a reduction in firm R&D to less than half. And this impact has increased substantially over time from around 1.1 in 1976-1991 to 1.7 in 2008-2018, representing an almost doubling of the impact of rivals' R&D on focal firm R&D investment.

Could the large coefficients be the result of estimation bias or of third factors that affect R&D of both the focal firm and rivals? As noted above, firms and their rivals likely experience common shocks that boost their R&D. This suggests an upward bias in the coefficients of rivals' R&D (rivals' R&D is correlated with the error term), which would mean that the true impact of rivals' R&D is even larger. In the Appendix (Tables A1-3), we present regressions where we instrument rivals' R&D using R&D tax cost. We also instrument firm revenue, which could be endogenous, using firm age as an instrumental variable. The coefficients obtained using instrumental variables are quite similar to the OLS coefficients and they also increase over time.

[7] Bessen and Wang (2024) run similar regressions with different sales measures and find similar results.

Another concern is that rivals' R&D might be correlated with third factors that affect R&D of both the focal firm and rivals. For instance, a rival with a large market share might tend to invest more in R&D and that market share might also reduce the prospects of the focal firm, leading it to reduce R&D. The IV regressions should exclude such effects. Nevertheless, in Appendix Table A5 we include a variety of other controls for manufacturing firms that relate to the relative market position of the focal firm: the focal firm's market share (which is one minus rivals' aggregate market share), the share of the firm's business that is outside of manufacturing, the firm's markup, and the firm's mean R&D tax cost.[8] These controls are statistically significant, but they do not diminish the coefficients on rivals' R&D, suggesting that rivals' R&D independently affects focal firm R&D and is more than just a proxy for rivals' market share, etc. We also tested specifications with controls for a variety of IO competition concerns.[9] All of these specifications still showed a statistically significant increase in the (negative) coefficient on rivals' R&D.

In the Appendix, we perform several additional robustness checks on this finding. These include checking the effects of imputed R&D, using reported worldwide R&D as the dependent variable, and using inverse propensity weights to adjust for sample truncation caused by the use of lagged rivals' R&D.

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[8] We can only measure these variables in manufacturing. Firm market share is the output-weighted market share of the firm's manufacturing establishments. Non-manufacturing share is the share of the firm's total employment outside of manufacturing. Markup is the output-weighted markup of the firm's establishments calculated using the Raval method for intermediate inputs. R&D tax cost is R&D-weighted mean of the firm's tax cost (state and Federal) from Barth et al. (Barth, Davis, Diethorn, et al. 2023).

[9] These included a flag for market leader; the market share of the industry's top four firms; flags for incumbent and entrant firms (< 5 year of age); flags for laggard and leader firms (below/above median TFP); and flags for neck & neck competition vs. "unlevelled" competition (below/above median industry markup; also, below/above industry TFP dispersion).

Our measure of technological rivalry corresponds to several common measures of industrial dynamism. Table 2, using 6-digit NAICS industry cross-sectional observations, shows several dynamism measures regressed against the industry mean level of technological rivalry and mean level of log R&D spending (using aggregate sample weights). We control for industry R&D levels because industry R&D may be correlated with technological rivalry and also with dynamism measures. We find that technological rivalry is associated with higher industry rates of firm births and deaths, with lower firm age, with lower industry concentration, measured either by the industry Hirschmann-Herfindahl Index or by the market share of the top four firms, and with higher rates of disruption of the top firms, measured as the probability that a firm found in the top four firms in one year is below the top four the next year. Thus, generally this measure of technological rivalry corresponds to common notions of industrial dynamism. And the industries with the highest levels of technological rivalry include the dynamic software and biotech industries (see Appendix Table A9). But our measure differs from some other measures of dynamism: our measure has increased substantially while other measures decreased (Decker et al. 2016, 2017, 2020).

Given the instrumental variable analysis, our measure of technological rivalry plausibly causes firms to substantially reduce their R&D investments. It might seem logical that firms also curtail other sorts of investment activity in the face of technological rivalry, including investing in firm growth. This we explore next. It is possible that the mechanism tying rivals' R&D to lower firm investment is something other than obsolescence risk. Perhaps rivals' R&D raises the price of R&D inputs or perhaps greater rivals' R&D creates more opportunities to imitate rivals with less own-firm investment. We don't think the

evidence supports these hypotheses,[10] but if it did, then we would not see a relationship between technological rivalry and slower growth below.

Firm Growth

First, we explore the relationship between establishment growth and multi-factor productivity in the manufacturing sector in Table 3. Column 1 shows the regression for equation (13).[11] The coefficient for rivals' R&D is positive, and the interaction between rivalry and TFP is negative and significant, implying that technological rivalry reduces the responsiveness to productivity. The bottom row shows the combined effect of these two terms on establishment growth; at the sample mean the effect is about -4 percent.

Decker et al. (2020) interact TFP with a trend term to see whether responsiveness changes over time. Column 2 adds an interaction between a trend term and TFP. We find a negative and significant trend, but the coefficients on the rivalry terms change little. Other factors appear to reduce establishment responsiveness to TFP in addition to technological rivalry. This could represent rising adjustment costs or it could represent the effects of changing markups or output elasticity (Biondi et al. 2025). Column 3 also tests trends in the rivalry coefficients, but these do not appear to change significantly over time. Finally, column 4 adds three possibly confounding variables: the markup, firm market share, and the

[10] R&D inputs are largely personnel, but scientists and engineers have not had rising wage premiums. And rivals' patents should limit imitation, but rival's patents do not significantly affect R&D demand (Bessen and Wang 2024; Ando et al. 2025).

[11] Note that the firm anticipates a_{t+1} from the TFP achieved in year *t*. Because Table 1 estimates $\hat{X}_{it}$ for the entire non-farm business sector, we do not use these estimates for analyzing the manufacturing sector specifically. We use $\text{asinh}\, S_{it-1}$ in lieu of $\hat{X}_{it} = -(\hat{\gamma}_S \cdot \text{asinh}\, S_{it-1} + \hat{\gamma}_x \cdot \text{asinh}\, S_{it-1} \cdot \ln R_{it})$. The second term of $\hat{X}_{it}$ is small in this sample so there is little difference in the results. The coefficients on log employment are omitted from the table to reduce the number of disclosed coefficients.

share of firm employment outside of manufacturing.[12] Again, these variables do not seem to alter the rivalry coefficients significantly, but they do eliminate the trend in the TFP coefficient. This finding is consistent with Biondi et al. for Europe who argue that rising markups reduce firm growth in European data. But the key takeaway is that technological rivalry is substantially related to slower establishment growth in response to productivity.

Table 4 expands the analysis to non-manufacturing industries; this is important because some of the strongest rivalry levels are outside manufacturing (see Appendix Table A9). Here, the analysis is at the firm level, and the productivity measure is simple revenue labor productivity, the log of real firm revenue per employee for the firm. Because revenue may have somewhat different meaning in finance, real estate, and insurance, we exclude these industries (NAICS 52 and 53). Using revenue data from LBDrev, this gives us 62 million firm-year observations from 1997 to 2018, excluding exiting firms, with an inverse propensity weight to make the analysis representative of the full LBD sample of firms with positive employment across the non-farm non-residential private sector. The regressions follow equation (13), omitting the display of coefficients for log employment. Standard errors are clustered by industry. The values of $\hat{X}_{it}$ are calculated from the regressions in Table 1.

Columns 1 and 2 of Table 4 show the estimates for the small sub-sample of firms in SIRD/BRDIS where we have data for the rivalry impact measure and the instrumented version of this measure. The coefficients on the rivalry measure interacted with productivity

[12] Markups are measured using the Raval method (2023b, 2023a) using materials. The output elasticities of materials are calculated for the 6-digit NAICS industries. Market share is the share of firm establishment in the shipments of all establishments in the 6- digit NAICS industry.

are negative and significant.[13] This echoes our finding presented above that firms facing greater obsolescence risk are less responsive to positive productivity shocks. The instrumented version is only slightly different. The instrumented version suggests that the impact of rivalry on firm growth is plausibly causal.

But this sample is too small to draw conclusions about aggregate job reallocation. To conduct the analysis on the full non-farm business sector, we impute the rivalry measure for firms where we do not have data. We first run a regression using the sample of firms for which the rivalry measure is available. The estimated rivalry measure obtained from regression in Table 1B for observations from 1997 to 2018 is regressed on the mean rivalry measure for the firm's 4-digit industry and time period, as well as on this measure interacted with the firm's log revenue (see Appendix Table A10). The regression coefficients are highly significant, with an adjusted R-squared above 0.95. We use these regression coefficients to predict dependent variable for firms in the full non-farm business sector and treat the predicted values as our imputed rivalry measure. Column 3 uses the imputed rivalry measure plus the imputed measure interacted with firm productivity. The coefficients for both are significantly negative implying that, all else equal, firms facing greater technological rivalry will grow more slowly and will respond less to productivity differences.

Decker et al. (2020; see also Cooper et al. 2024) conduct a similar regression using a trend term interacted with firm productivity. They find a negative coefficient for this interaction term and discuss possible trends that might account for it. Their preferred explanation is rising labor adjustment costs which prevent productive firms from expanding

[13] We omit the non-interacted term for X_{it} in this regression because it is highly correlated with the interacted term. In this small sample, including both terms make neither significant. We include the non-interacted term in columns 3-5 where the samples are much larger.

their business. To explore whether our rivalry measure might be picking up another factor sharing a common trend, column 4 adds a trend interaction term to the regression. The coefficient on the rivalry term interacted with productivity is slightly smaller (less negative), but still negative and significant. The trend term is also negative and significant, suggesting that other trending factors might also be in play, but with a much smaller role.

As can be seen in each column, young firms (those under 5 years of age) tend to grow faster, all else equal. High rivalry industries also tend to have more young firms. To check that the age composition of industries does not influence our results, column 5 adds a term interacting the young dummy variable with the rivalry measure times productivity. The coefficient shows that the effect of rivalry on productive young firms is smaller; this coefficient is statistically significant, but economically small, suggesting that age composition is not a concern.

Reallocation

We can calculate the effect of technological rivalry on firm growth for each firm as

$$D_{it} = \hat{\theta}_X X_{it} + \hat{\theta}_z X_{it} \ln A_{it} \,. \tag{15}$$

Table 5 shows the sample mean value for two time periods, 1997-2007 and 2008-2018 using coefficient values from Table 4, column 3. The second row shows that technological rivalry appears to have a substantial negative effect on firm growth that has increased between the two periods. At the sample mean, it decreases firm growth by about 10 percent during the first period and about 15 percent during the second.

We can explore this impact using counterfactual growth by backing out the difference attributed to technological rivalry:

$$g'_{it} = g_{it} - D_{it}, \qquad e'_{it+1} = e_{it} \frac{2 + g'_{it}}{2 - g'_{it}}. \tag{16}$$

The counterfactual growth (g'_{it}) is a hypothetical growth rate of firms without the rivalry effect. The counterfactual forward employment (e'_{it+1}) is a hypothetical employment level without the rivalry effect and is derived from the equation for DHS growth. These variables are used to compute the job reallocation effect in a counterfactual economy.

At the firm level, Figure 2 shows the relationship between actual and counterfactual firm growth with productivity in a binned scatterplot. The x-axis shows revenue labor productivity; the y-axis shows mean DHS growth rates for the different bins. The top panel shows actual growth for 1997 (solid) and 2018 (dashed). The positive slope shows that higher-productivity firms yield higher growth rates. The slope of the line is less steep in 2018, indicating a lower growth response to productivity. The lower panel shows the counterfactual growth rates for the two years. Except for the lowest productivity bins, the lines are roughly parallel, implying that for most firms, technological rivalry can account for the decline in responsiveness observed in the top panel.

Following Decker et al. (2020), we can formalize this observation by calculating the aggregate rate of job reallocation. The aggregate rate of job reallocation at time *t* (J_t) is computed as a weighted sum of job reallocation effects at the firm level (g_{it}):

$$J_t = \sum_i s_{it} \cdot |g_{it}|, \quad s_{it} = \frac{e_{it} + e_{it+1}}{\sum_j (e_{jt} + e_{jt+1})} \tag{17}$$

where s_{it} is the firm's share of employment over the current and next year.[14] We calculate the counterfactual job reallocation as:

$$J'_t = \sum_i s'_{it} \cdot |g'_{it}|, \quad s'_{it} = \frac{e_{it} + e'_{it+1}}{\sum_j (e_{jt} + e'_{jt+1})}. \tag{18}$$

[14] The actual calculation includes inverse propensity weights.

Table 5 shows both measures for each time period. Consistent with the literature, the actual rate of job reallocation, shown in the third row, fell substantially from 19 percent in the first period to 15 percent in the second. But counterfactual job reallocation changed little: from 23.8 percent to 22.9 percent. This suggests that most of the decline in job reallocation can be accounted for by the impact of technological rivalry.

5. Conclusion

Many economists view competition as central for spurring innovation that generates productivity growth (Gilbert 2006; Shapiro 2011). Evidence of rising industry concentration (e.g., Autor et al. 2020) and rising markups (e.g., De Loecker et al. 2020) has led some economists to conclude that competition is declining in the US, although that view is contested (Berry et al. 2019; Shapiro and Yurukoglu 2026). But markups and industry concentration are about price competition, either directly or indirectly. This paper argues that technological competition, measured by the effect of rivals' R&D expenditures, is something quite different. First, technological rivalry has been rising strongly. Second, technological rivalry appears to *reduce* reallocation. Greater technological rivalry reduces the likelihood that firms respond to productivity shocks at all, and when they do respond, they grow more slowly in the face of greater technological rivalry. While other factors such as labor market frictions surely contribute to slower response, most of the decline in aggregate job reallocation can be accounted for by rising technological rivalry.

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Tables

Table 1. Measuring Technological Rivalry via R&D Demand

Dependent variable: Log R&D				
	(1)	(2)	(3)	(4)
Period	1977-1991	1992-1999	2000-2007	2008-2018
A. Regression without revenue terms				
Asinh(rival $R\&D_{t-1}$)	-0.288*	-1.486***	-2.156***	-1.884***
	(0.147)	(0.178)	(0.196)	(0.183)
Adjusted R^2	0.338	0.461	0.339	0.207
Observations	20,500	13,000	17,500	35,000
B. Regression with revenue terms				
	(1)	(2)	(3)	(4)
Rivals' lagged R&D (asinh)	-0.169	-0.811***	-1.075**	-1.844***
	(0.477)	(0.313)	(0.463)	(0.303)
Log revenue x rivals' R&D (asinh)	-0.016	0.026	0.030	0.083***
	(0.048)	(0.022)	(0.032)	(0.022)
Foreign = 0 x log revenue	0.772***	0.728***	0.650***	
	(0.148)	(0.060)	(0.067)	
Foreign = 1 x log revenue	0.898***	0.784***	0.707***	
	(0.155)	(0.058)	(0.067)	
Log revenue				0.416***
				(0.043)
Adjusted R-squared	0.648	0.74	0.724	0.581
N (rounded)	25000	19500	28500	50000
Mean impact ($\overline{X_{it}}$)	1.072	0.900	1.333	1.701

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry and year and use time-consistent sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. The mean impact is calculated as $-\left(\gamma_S \cdot \overline{\operatorname{asinh} S_{it}} + \gamma_x \cdot \overline{\operatorname{asinh} S_{it} \cdot \ln R_{it}}\right)$ where the bars signify sample means. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table 2. Industry Dynamism Measures and Technological Rivalry

Naics6 industry means, 2003-2018

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Firm birth rate	Firm death rate	Firm Age	Mean HHI	Mean CR4	Mean rate of disruption
Technological rivalry (X)	0.017***	0.009***	-3.768***	-0.054***	-0.124***	0.125***
	(0.003)	(0.002)	(0.433)	(0.010)	(0.019)	(0.010)
Mean Ln real R&D	-0.003***	-0.002***	0.463***	0.022***	0.061***	-0.007***
	(0.000)	(0.000)	(0.074)	(0.002)	(0.003)	(0.002)
Adjusted R^2	0.051	0.052	0.094	0.180	0.302	0.154
N	800	800	800	800	800	800

Note: Standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Regressions use sample weights. Disruption rate is the probability that a firm ranked in the top 4 of the industry by sales is not in the top for the subsequent year. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12510).

Table 3. Establishment Growth and Technological Rivalry,

Manufacturing

Dependent variable: DHS establishment growth rate, continuing and exiting establishments 1977-2018

	(1)	(2)	(3)	(4)
Establishment TFP	0.267***	0.300***	0.321***	0.276***
	(0.030)	(0.031)	(0.036)	(0.029)
Rivals' R&D	0.039**	0.041**	0.053**	0.040**
	(0.019)	(0.019)	(0.025)	(0.018)
TFP x Rivals' R&D	-0.021***	-0.022***	-0.029***	-0.019***
	(0.008)	(0.008)	(0.010)	(0.007)
Year x TFP		-0.004***	-0.006***	0.001
		(0.001)	(0.002)	(0.001)
Year x Rivals' R&D			-0.001	
			(0.002)	
Year x Rivals' R&D x TFP			0.001	
			(0.001)	
Markup				-0.057***
				(0.006)
Market share				0.05
				(0.036)
Non-manufacturing share (firm)				-0.042***
				(0.013)
Adjusted R-squared	0.103	0.103	0.103	0.118
N (rounded)	656000	656000	656000	628000
Mean rivalry effect	-0.0399	-0.0398		-0.0187

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Coefficients on employment terms not shown. Regressions use sample weights and industry by year fixed effects. TFP is calculated using the Levinsohn-Petrin method and rivals' R&D is $\operatorname{asinh} S_{it-1}$. Markups are measured using the Raval method using materials. Market share is the share of the establishment in the shipments of all establishments in the 6- digit NAICS industry. The mean rivalry effect is $\theta_z \overline{X} \cdot \overline{\ln TFP} + \theta_X \overline{X}$ taken at the sample means. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12510).

Table 4. Firm Growth and Technological Rivalry, Non-farm Business Sector

Dependent variable: DHS firm growth rate for continuing firms

	(1)	(2)	(3)	(4)	(5)
Log LP	0.050***	0.045***	0.121***	0.137***	0.121***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)
Rival impact (X) x log LP	-0.003***				
	(0.001)				
Rival impact IV x log LP		-0.003***			
		(0.001)			
Imputed rival impact (X)			-0.070**	-0.086***	-0.088***
			(0.030)	(0.030)	(0.031)
Imputed rival impact x log LP			-0.020***	-0.018***	-0.023***
			(0.004)	(0.004)	(0.004)
Young (age<5)	0.049***	0.049***	0.030***	0.030***	0.020***
	(0.010)	(0.010)	(0.002)	(0.002)	(0.003)
Year x log LP				-0.002***	
				(0.000)	
Young x imputed rival impact x log LP					0.003***
					(0.000)
Adjusted R-squared	0.039	0.039	0.094	0.094	0.094
N (rounded)	51000	51000	62090000	62090000	62090000
period	2000-2018	2000-2018	1997-2018	1997-2018	1997-2018

Note: Labor productivity (LP) is measured by revenue/employee. Firms in non-agricultural private business sector excluding NAICS 52 and 53 from 1997 to 2018. Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Coefficients on employment terms not shown. Regressions include fixed effects for 6-digit industry by year and state. Regressions use inverse propensity weights. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table 5. Aggregate Job Reallocation

Period	1997-2007	2008-2018
Mean rival impact (X)	0.624	0.868
Mean effect of rivalry (D)	-0.105	-0.147
Job reallocation	0.186	0.150
Job reallocation (counterfactual)	0.238	0.229

Note: The rivalry effect (X) is defined in equation (2). The effect of technological rivalry on firm growth (D) is defined in equation (15). The weighted average of these two variables, using inverse propensity weights, is shown in the first two columns. Job reallocation is a weighted average of the absolute value of the employment growth rate at the firm level, as defined in equation (17). The counterfactual calculation without the rivalry effect is defined in equation (18).

Figure 1. Solution Zones

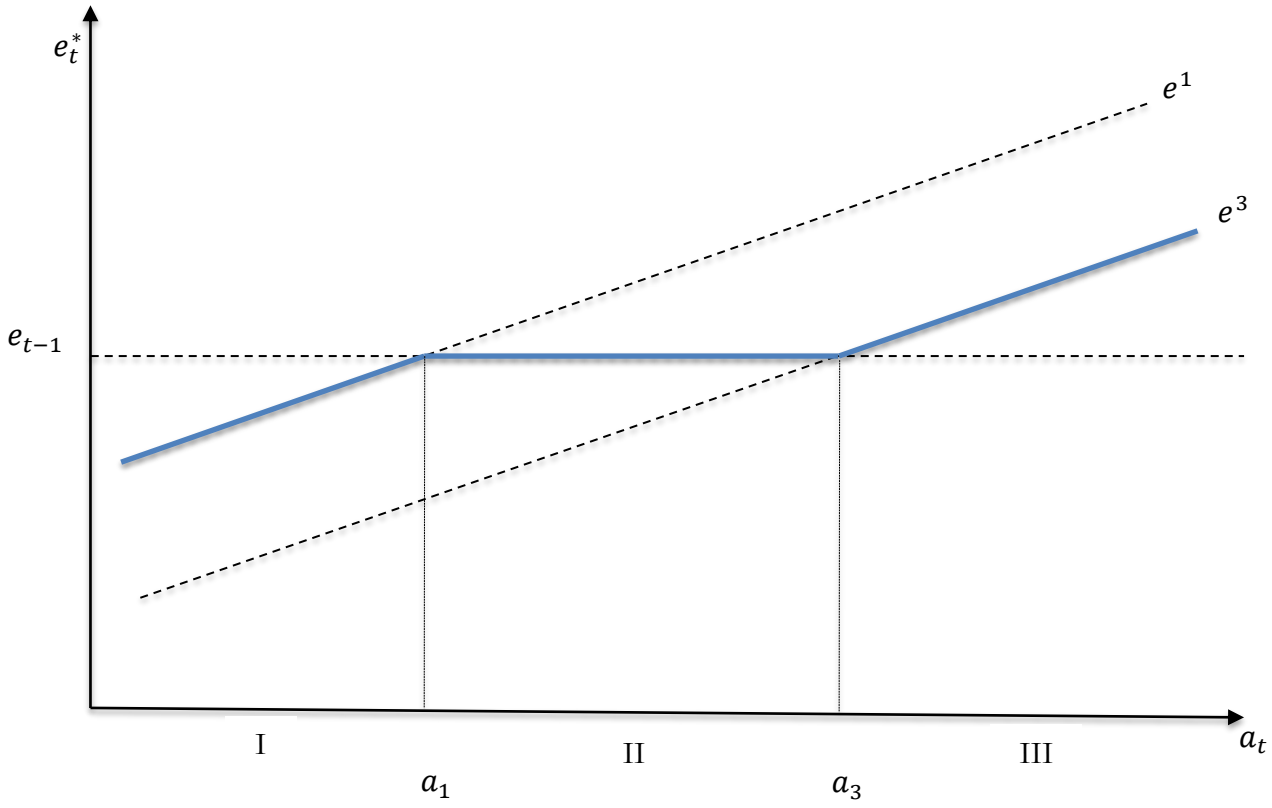
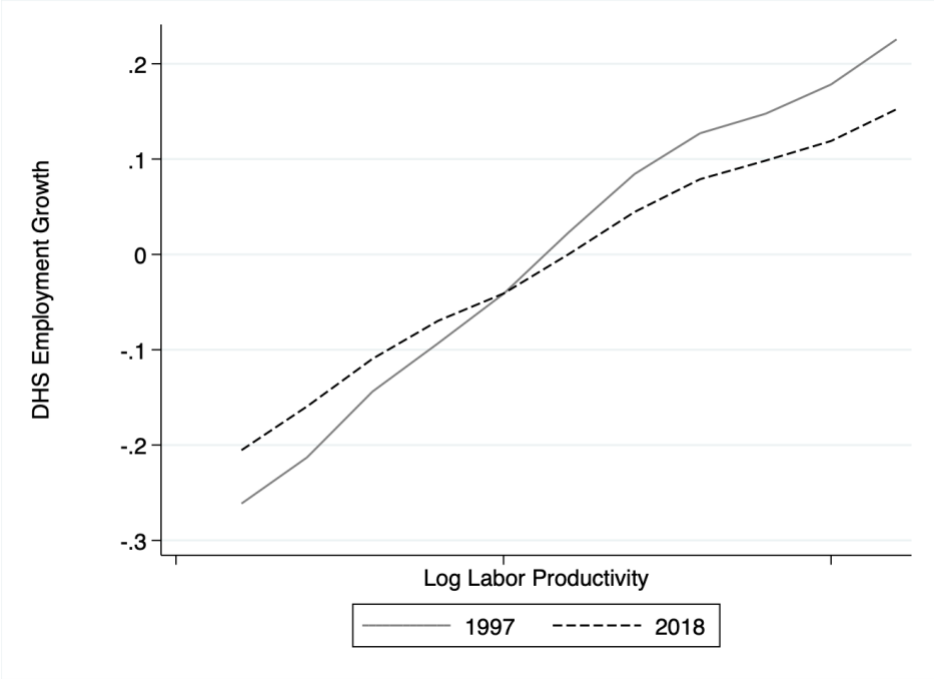
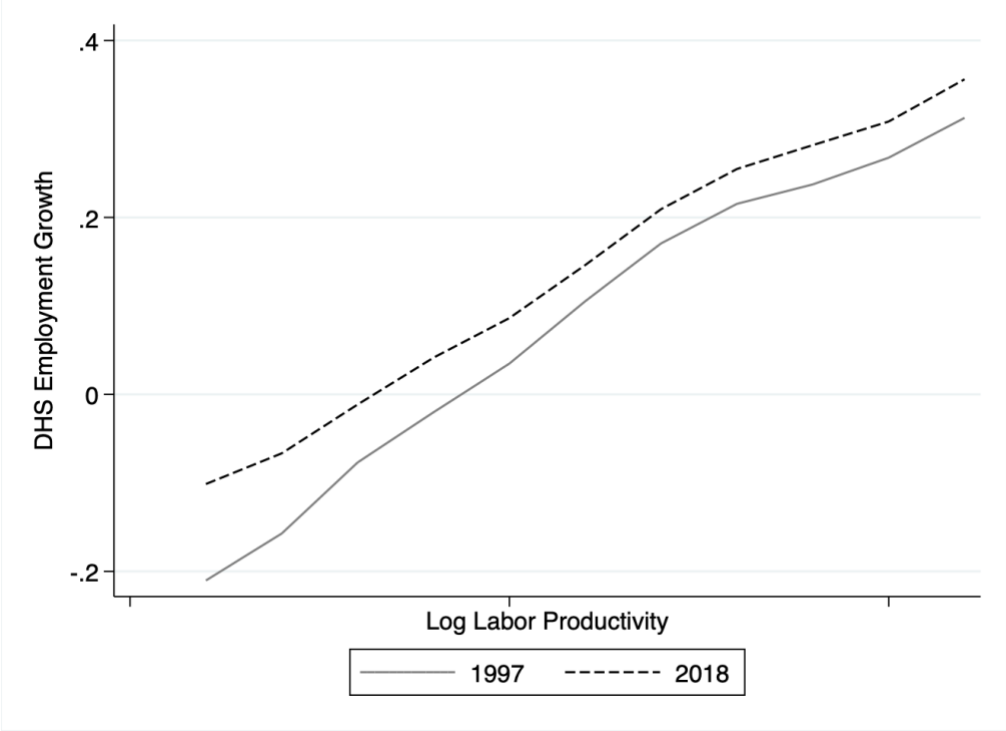


Figure 2. Firm Growth and Productivity

A. Actual Employment Growth



B. Counterfactual Employment Growth



Appendix

1. Instrumental variable estimations

One concern with our investment regressions is that technology shocks might be correlated with both a firm's investment and its rivals' investments, leading to a spurious correlation. Since this would be a positive correlation, it would tend to weaken our results, that is, the true coefficient on rivals' investment would be more negative that our estimate. Nevertheless, to control for this or related endogenous effects, we lag rivals' investment and we instrument it following Bloom et al. (2013; see also Lucking et al. 2019). The instrument we use is the log of the tax term in Jorgensonian R&D user cost as developed by Wilson (2009),

$$\rho_{it} = \frac{1 - A^c_{st} - A^c_{ft} - A^d_{st} - A^d_{ft}}{1 - \tau^e_{st} - \tau^e_{ft}}, \quad s = state, f = Federal$$

where A^c is the present value of R&D investment tax credits, A^d is the present value of R&D depreciation allowances, and τ^e is the effective tax rate. The Jorgensonian user cost of R&D is then $\rho_{it} P_t^{R\&D}(r_t + \delta)$, where $P_t^{R\&D}$ is the price of R&D services, r_t is the interest rate, and δ is the depreciation rate. We use data on state and federal tax credits developed by Barth et al. (2023). We find that log R&D tax price is a reasonably good predictor of R&D. In the first stage regression, log R&D is regressed on log R&D tax price and firm fixed effects, and the predicted value is used as predicted R&D. The relationship between the original measure of rivalry R&D and the predicted value is shown in column 1 of Table A1. The IV regressions of the investment demand equation are shown for two periods in columns 2 and 3, corresponding to columns 3 and 4 of Table 1 in the main text.

There is a possible bias with this approach however: to the extent that rivals invest in the same state as the subject firm, the exclusion restriction might be violated. That is, that state's R&D tax price would influence both the dependent variable and our predicted measure of rival investment. First, in column 4 of Table A2 we check whether our instrumented variable is, in fact, correlated with the focal firm's R&D tax price. The association is not significant. Then in columns 5 and 6, we repeat the regressions but now include log R&D tax price on the right hand side to inoculate against this bias. While the log R&D tax price coefficient is significant and negative, as expected, the effect on the coefficient of rivals' R&D is minimal.

As a further robustness check, Table A2 shows regressions where we construct the instrumental variable to exclude R&D that occurs in the same state as the focal firm's R&D. Column 1 shows the relationship between the original measure of rivalry R&D and the predicted value, and columns 2 and 3 show the investment demand regressions. These results are similar also, suggesting that same-state contamination is not a problem.

Finally, Table A3 uses both instrumented rivals' R&D and instrumented focal firm revenue. We predict firm revenue by firm age plus a firm fixed effect. The values of the coefficients on rivals' R&D are similar.

Table A1. Supplementary Instrumental Variable Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	asinh(rival R&D)	ln(R&D)	ln(R&D)	asinh(rival R&D; IV1)	ln(R&D)	ln(R&D)
asinh(rival R&D; IV1)	0.814***	-0.772***	-1.830***		-0.761***	-1.822***
	(0.00356)	(0.270)	(0.293)		(0.270)	(0.293)
log(revenue) x asinh(rival R&D; IV1)		0.0169	0.0828***		0.0163	0.0828***
		(0.0189)	(0.0202)		(0.0189)	(0.0201)
log (R&D tax price)				0.0248	-1.570***	-1.847***
				(0.0420)	(0.579)	(0.441)
Adjusted R-squared	0.961	0.742	0.608	0.902	0.743	0.61
N (rounded)	66000	24500	41500	66000	24500	41500
period	2000-2018	2000-2007	2008-2018	2000-2018	2000-2007	2008-2018
Mean impact ($\overline{X}_{it}$)		1.197	1.886			

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry (except for column 1) and year and use time-consistent sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. Rival R&D (IV1) is the sum of predicted R&D by rival firms based on the R&D tax price of R&D. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table A2. IV regressions with same observations from same state excluded from instrument

	(1)	(2)	(3)
	asinh(rival R&D)	log(R&D)	log(R&D)
asinh(rival R&D; IV2)	0.778***	-0.771***	-1.704***
	(0.0106)	(0.254)	(0.248)
log(revenue) x asinh(rival R&D; IV2)		0.0187	0.0801***
		(0.0177)	(0.0186)
Adjusted R-squared	0.902	0.743	0.609
N (rounded)	66000	24500	41500
period	2000-2018	2000-2007	2008-2018

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry (columns 2 and 3) and year and control for revenue (in column 3; revenue interacted with Foreign=1 in column 2) and use time-consistent sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. Rival R&D (IV2) is the sum of predicted R&D by rival firms, where rival firms in the same state as focal firms are excluded. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table A3. Regressions with predicted value of rivals' R&D and firm revenue

	(2)		(3)	
Dependent variable	ln(R&D)		ln(R&D)	
asinh(rival R&D; IV1)	-0.910***		-1.325***	
	(0.256)		(0.271)	
log(revenue;IV) x asinh(rival R&D; IV1)		0.0239	0.0600***	
	(0.0181)		(0.0200)	
log(revenue;IV)	0.763***		0.587***	
	(0.0380)		(0.0426)	
	-0.910***		-1.325***	
Adjusted R-squared		0.726		0.651
N (rounded)		25000		41500
period	2000-2007		2008-2018	

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry (except for column 1) and year and use time-consistent sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. Rival R&D (IV1) is the sum of predicted R&D by rival firms based on the R&D tax price of R&D. Revenue is instrumented by regressing firm real revenue on firm age and a firm fixed effect. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

2. Regression Bias from Construction of Rivalry Measure

In the investment demand equation (7), the dependent variable, $\ln I_{it}$, is implicitly related to the rivalry measure and that can cause a bias in the coefficient estimate for S_{it}. We can see this by "partialing out" these variables, that is, using the residuals of these two variables after regressing them on other independent variables, including fixed effects and the constant term. Then the basic regression can be written in simplified form as

$$\ln I_{it} = \beta S_{it-1} + \epsilon_{it}, \quad S_{it-1} = \ln(T_{t-1} - I_{it-1}), \quad T_t = \sum_j I_{jt} \qquad (A1)$$

where I_{it} is the real R&D made by firm *i* at time *t* in a given industry, T_{t-1} is the sum of these investments over all firms in that industry at time *t*-1, and S_{it-1} is our rivalry measure.

There is a potential estimation problem because the construction of S_{it-1} involves I_{it-1} which likely covaries with the dependent variable. We can see this by looking at the OLS estimator,

$$\hat{\beta} = \frac{cov(\log I_{it}, S_{it-1})}{var(S_{it-1})}. \qquad (A2)$$

To see the bias, it is helpful to decompose the error term in (A1) into two parts,

$$\epsilon_{it} = \phi_i + \theta_{it} \qquad (A3)$$

where although $E[\epsilon_{it}] = 0$, possibly

$$cov(\theta_{it}, \theta_{jt}), cov(\theta_{it}, \theta_{it-1}) \neq 0.$$

Plugging (A1) and (A3) into (A2), the OLS estimate is

$$\hat{\beta} = \frac{cov(\beta S_{it-1}, S_{it-1}) + cov(\phi_i, S_{it-1}) + cov(\theta_{it}, S_{it-1})}{var(S_{it-1})} = \beta + B,$$

$$B \equiv \frac{cov(\phi_i, S_{it-1})}{var(S_{it-1})} + \frac{cov(\theta_{it}, S_{it-1})}{var(S_{it-1})}. \qquad (A4)$$

B is thus the bias. We expect that the first term in the bias is negative, and the second term is positive. Decomposing the first term, we can see that it is negative:

$$cov(\phi_i, S_{it-1}) = cov\left(\phi_i, \log T_{t-1} + \log\left(1 - \frac{I_{it-1}}{T_{t-1}}\right)\right) \approx -cov\left(\phi_i, \frac{I_{it-1}}{T_{it-1}}\right) < 0 \quad (A5)$$

since $cov(\phi_i, \log T_{t-1}) = 0$ and $\log(1+x) \approx x$ for small *x*. The second term in the numerator, $cov(\theta_{it}, S_{it-1})$, is likely greater than zero because firms within an industry experience common shocks in R&D demand (shocks to business conditions, technological opportunities) that are serially correlated. Hence the net bias could be either positive or negative. Note that this bias only affects the investment demand equation and does not come into play in the regressions on whether firms choose to invest or not.

Fortunately, we can estimate the magnitude of this bias by proxying ϕ_i with the sample mean of $\log I_{it}$ for each firm, $\overline{\log I_\iota} = \frac{1}{T}\sum_t \log I_{it}$. We can show that[15]

$$\frac{cov(\phi_i, S_{it-1})}{var(S_{it-1})} \approx -\frac{cov\left(\overline{\log I_\iota}, \frac{I_{it-1}}{T_{it-1}}\right)}{var(S_{it-1})} + \beta\frac{var\left(\overline{\frac{I_\iota}{T_\iota}}\right)}{var(S_{it-1})}. \quad (A6)$$

We estimate the first term on the right and find it is small relative to the coefficient estimates for both R&D (see Table). We also estimate $var\left(\overline{\frac{I_\iota}{T_\iota}}\right)/var(S_{it-1})$ and find that it, too, is small but positive, reducing the net negative bias further. Relative to the estimates of $\hat{\beta}$ from Table 1, the negative bias in (A4) is less than 10% except for the first period. Moreover, it is offset by the positive bias term, $cov(\theta_{it}, S_{it-1})$. Hence, we do not think that the net bias substantially affects our results, so we ignore it in the main paper.

Table A4. Bias estimates

	$-\frac{cov\left(\overline{\log I_\iota}, \frac{I_{it-1}}{T_{it-1}}\right)}{var(S_{it})}$	$\frac{var\left(\overline{\frac{I_\iota}{T_\iota}}\right)}{var(S_{it})}$
1977-1991	-.243	.068
1992-1999	-.063	.074
2000-2007	-.074	.086
2008-2018	-.095	.069

Note: These estimates are calculated on the samples for Table 4. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

3. Bellman Solution

Using the probabilities $P_j, j = 1,2,3,$

[15] From (A1) and (A3), $\log I_{it} = \beta S_{it-1} + \phi_i + \theta_{it}$ so that $\overline{\log I_\iota} = \beta\overline{S_\iota} + \phi_i$ since $E[\theta_{it}] = 0$. Further, following the analysis in (A5), $\overline{S_\iota} \approx \overline{\log T_\iota} - \overline{\left(\frac{I_\iota}{T_\iota}\right)}$. Note also that $cov\left(\overline{\left(\frac{I_\iota}{T_\iota}\right)}, \frac{I_{it-1}}{T_{it-1}}\right) \approx var\left(\overline{\frac{I_\iota}{T_\iota}}\right)$ so that $cov\left(\overline{\log I}, \frac{I_{it-1}}{T_{it-1}}\right) \approx cov\left(\phi_i, \frac{I_{it-1}}{T_{it-1}}\right) - \beta var\left(\overline{\frac{I_\iota}{T_\iota}}\right)$.

$$\mathbb{E}[\pi_t] = P_1\mathbb{E}[R(A_t, E_t) - WE_t] + P_2\mathbb{E}[R(A_t, E_{t-1}) - WE_{t-1}] + P_3\mathbb{E}[R(A_t, E_t) - WE_t - T(E_t - E_{t-1})].$$

Then it is helpful to expand the Bellman equation recursively,

$$V(E_{t-1}) = \max_{E_t}[\pi_t + B\mathbb{E}[\pi_{t+1}] + B^2\mathbb{E}[\pi_{t+2}] + \cdots]$$

and take the first order condition to maximize the term in brackets,

$$\frac{\partial R(A_t, E_t)}{\partial E_t} - W - T \cdot \mathbb{I}[E_t > E_{t-1}] + BP_3T + BP_2\mathbb{E}\left[\frac{\partial R(A_{t+1}, E_t)}{\partial E_t} - W\right] + B^2P_2^2\mathbb{E}\left[\frac{\partial R(A_{t+2}, E_t)}{\partial E_t} - W\right] + \cdots = 0.$$

Since $\mathbb{E}[\ln A_{t+n}] = \ln A_t$, $\mathbb{E}[A_{t+n}] \approx A_t$.[16] Also, since $R(A_t, E_t)$ is linear in A_t, $\mathbb{E}[R_{t+n}] \approx R_t$. Using this and reducing the infinite sum yields a first order condition

$$\frac{\partial R(A_t, E_t)}{\partial E_t} = (1 - BP_2)(W + T \cdot \mathbb{I}[E_t > E_{t-1}] + BP_3T). \quad (A7)$$

Applying this to our three solution zones

$$E_t^* = \begin{cases} E^1, & E^1 < E_{t-1} & I \\ E_{t-1}, & E^1 \le E_{t-1} \le E^3 & II \\ E^3, & E^3 > E_{t-1} & III \end{cases}$$

where $E^1 \equiv \left(\frac{\phi A_t}{W - TBP_3(1-BP_2)}\right)^{\frac{1}{1-\phi}}$, $E^3 \equiv \left(\frac{\phi A_t}{W + T(1-BP_3)(1-BP_2)}\right)^{\frac{1}{1-\phi}}$. Since our empirical exploration concerns the relationship between employment and productivity, we can describe the firm's optimal behavior as a function of its productivity draw. Using lower case variables to designate logs, $e = \log E$, $a = \log A$, define

$$a^1 = (1-\phi)e_{t-1} + \ln\left(\frac{1}{\phi}\left(W - TBP_3(1-BP_2)\right)\right) \quad (A8)$$

$$a^3 = (1-\phi)e_{t-1} + \ln\left(\frac{1}{\phi}(W + T(1-BP_3)(1-BP_2))\right)$$

so that

$$e_t^* = \begin{cases} e^1, & a_t < a^1 & I \\ e_{t-1}, & a^1 \le a_t \le a^3 & II \\ e^3, & a^3 > a_t & III \end{cases}. \quad (A9)$$

[16] For instance, if we assume a lognormal distribution for ν with $\sigma = .28$ as in Decker et al. (Appendix Table A1, 2020), then $\mathbb{E}[A_{t+n}]$ is 3.9 percent larger than A_t.

4. Supplementary Tables

Table A5. R&D Investment and Technological Rivalry, Additional controls

	(1)	(2)	(3)	(4)
Period	1977-1991	1992-1999	2000-2007	2008-2018
Dependent variable: Log R&D				
Asinh(rival $R\&D_{t-1}$)	-1.419***	-1.024***	-1.145***	-2.430***
	(0.391)	(0.257)	(0.366)	(0.375)
log(revenue) × asinh(rival $R\&D_{t-1}$)	0.100***	0.041**	0.04	0.147***
	(0.031)	(0.018)	(0.026)	(0.026)
Foreign = 0 × log(revenue)	0.491***	0.664***	0.627***	
	(0.117)	(0.051)	(0.059)	
Foreign = 1 × log(revenue)	0.550***	0.706***	0.666***	
	(0.117)	(0.050)	(0.059)	
log(revenue)				0.166***
				(0.052)
Firm market share	6.599***	3.530***	2.940***	7.478***
	(1.116)	(0.687)	(0.596)	(0.895)
Non-manufacturing share	0.991***	0.820***	1.098***	1.647***
	(0.279)	(0.251)	(0.203)	(0.197)
Markup	0.025	0.195***	0.130**	0.225***
	(0.111)	(0.069)	(0.059)	(0.047)
R&D tax cost	0.749	-2.118***	-1.476**	-1.548**
	(1.325)	(0.771)	(0.571)	(0.677)
Adjusted R^2	0.742	0.745	0.741	0.612
Observations	17,000	11,000	14,000	20,000

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry and year and use adjusted sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. Firm market share is the output-weighted market share of the firm's establishments. Non-manufacturing share is the share of the firm's total employment outside of manufacturing. Markup is the output-weighted markup of the firm's establishments calculated using the Raval method for intermediate inputs. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

Table A6. Effect of imputation of R&D

Dependent variable: log(R&D)

	(1)	(2)
asinh(rival R&D)	-1.844***	-1.814***
	(0.303)	(0.300)
log(revenue) x asinh(rival R&D)	0.0829***	0.0819***
	(0.0220)	(0.0216)
log(revenue)	0.416***	0.414***
	(0.0428)	(0.0424)
Imputed = 1 x asinh(rival R&D)		-0.254***
		(0.0369)
Adjusted R-squared	0.581	0.582
N (rounded)	50000	50000
period	2008-2018	2008-2018

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry and year and use time-consistent sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. A binary variable Imputed=1 indicates that R&D is imputed in the SIRD and BRDIS datasets based on data obtained from an alternative source or values of other data items. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table A7. Base regressions with world R&D

Dependent variable: log(world R&D)

	(1)	(2)	(3)	(4)
asinh(R&D)	-0.151	-0.746**	-1.076**	-1.792***
	(0.472)	(0.313)	(0.449)	(0.303)
log(revenue) x asinh(R&D)	-0.0172	0.0224	0.0331	0.0858***
	(0.0479)	(0.0225)	(0.0309)	(0.0222)
Adjusted R-squared	0.65	0.746	0.735	0.601
N (rounded)	25000	19500	28500	50000
period	1977-1991	1992-1999	2000-2007	2008-2018

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry and year and control variables for Foreign = {0,1} x revenue as in Table 1 and use time-consistent sample weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Inverse propensity weights for lagged R&D

Because we use lagged rivals' R&D, we lose some observations that are not in the sample for the lagged year. To correct for this, we create an inverse propensity weight. We estimate the probability that a firm will not have lagged data using the firm's size class and detailed industry. We then use the inverse of this probability times the rebased sample weight to weight the regressions. These estimates (Table A7) seem more volatile, but nevertheless confirm the picture of a sharp increase in the impact of rivals' R&D.

Table A8. Base regressions with inverse propensity weights
Dependent variable: Log R&D

	(1)	(2)	(3)	(4)
asinh(rival R&D)	-0.0842	-1.319**	-1.052**	-1.984***
	(0.534)	(0.644)	(0.440)	(0.314)
log(revenue) x asinh(rival R&D)	-0.0244	0.0674	0.0301	0.105***
	(0.0545)	(0.0443)	(0.0314)	(0.0224)
Adjusted R-squared	0.657	0.774	0.71	0.564
N (round)	25000	19500	28500	50000
period	1977-1991	1992-1999	2000-2007	2008-2018

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects for 6-digit industry and year and control for Foreign = {0,1} x revenue as in Table 1 and use inverse propensity weights. Rivals' investment is lagged investment of all other firms in the same 6-digit industry. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table A9. Top 10 Industries by Technological Rivalry

Industry NAICS code	Industry name	Mean X
5417	Scientific Research and Development Services	2.489
5112	Software Publishers	2.432
5182	Data Processing, Hosting, and Related Services	2.191
5191	Other Information Services	2.143
5415	Data Processing, Hosting, and Related Services	2.104
4242	Drugs and Druggists' Sundries Merchant Wholesalers	2.082
4236	Household Appliances and Electrical and Electronic Goods Merchant Wholesalers	2.025
5511	Management of Companies and Enterprises	1.917
4234	Professional and Commercial Equipment and Supplies Merchant Wholesalers	1.857
3254	Pharmaceutical and Medicine Manufacturing	1.833

FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

A10. Imputing Rivals' Impact

We use the prediction from the following regression to impute technological rivalry X.

	(1)
Dependent variable	rivals' effect (X_{it})
Mean (rivals' effect)	1.527***
	(0.0790)
Mean (rivals' effect) x log(revenue)	-0.0492***
	(0.00577)
Adjusted R-squared	0.952
N (rounded)	67000
period	1997-2018

Note: Standard errors are shown in parentheses and are clustered by 4-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Mean (rivals' effect) is an average in the 4-digit industry. Regressions include fixed effects for 4-digit industry and year. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743).

Table A11. Levinsohn-Petrin Production Function Estimates

Labor	0.2428
Capital	0.1836
Intermediate inputs	0.5126

Note: A Stata command prodest is used to estimate a production function, log(q) = coeff_labor x log(labor) + coeff_capital x log(capital) + coeff_intermediate x log(intermediate) + error term, separately for each 3-digit NAICS industry. Here, the average of all 3-digit industries in the manufacturing sector is reported. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).