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

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Abstract: In "creative destruction," firms with productive innovations grow faster, replacing incumbents. Technological rivalry raises aggregate productivity through reallocation. But greater technological rivalry means that innovators themselves are subject to greater obsolescence risk, slowing their expansion. This paper explores whether technological rivalry slows firm growth and reallocation. Using microdata from the US Census, we measure technological rivalry, finding that firms facing greater rivalry are less likely to respond to productivity shocks and they respond more slowly. Estimating counterfactual firm growth from 1997-2018, rising technological rivalry can account for the declining response of firms to productivity shocks and declining job reallocation.

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1. Introduction

In Schumpeter's "creative destruction," firms introduce new, more productive technologies that replace less productive incumbent technologies. Resources shift to the more productive firms and this reallocation provides an important component of aggregate growth. (Foster et al. 2001, 2008, 2016; Baqaee and Farhi 2020). More productive firms enter new markets and grow faster, while less productive firm grow more slowly or exit. In this way, industrial dynamism helps translate productive innovations into productivity growth.

Yet there is an important downside to creative destruction: new technologies are themselves subject to obsolescence risk. Firms deciding to expand production, to enter new markets, or to adopt new technology will weigh the costs of these investments against the expected stream of future profits and that stream is affected by the obsolescence rate. A firm facing a greater risk of obsolescence may slow its investments in new technology, and the pace of reallocation will consequently slow.

This is important because evidence points to a substantial decline in the pace of reallocation. Decker et al. (2020) find that firms do not respond to productivity shocks as much as they did in the past; firms with productive innovations do not apparently grow as fast. Figure 2A illustrates this slowdown using binned data from the nonfarm business sector. The x-axis shows firm labor productivity for each bin (real revenue per employee); the y-axis shows the mean DHS growth rate for each bin (the DHS growth rate is described below). From 1997 to 2018 the slope of the curve fell significantly. The growth rate of the most productive group of firms fell from 23 percent per year to 15 percent, corresponding to substantially slower reallocation along with shifts for other bins. Decker et al. present supporting evidence that the pace of "job reallocation"—the churn of jobs from one firm to another—has also slowed (see also Hyatt and Spletzer 2013; Davis and Haltiwanger 2014;

Biondi et al. 2025). They suggest that labor adjustment costs may have risen, decreasing firm responsiveness (see also Cooper et al. 2024).[1]

This paper explores whether rising technological rivalry may have contributed to declining reallocation of productive resources. We begin with a model relating firm productivity to firm employment growth. When new technology involves hiring costs for training or adaptation, firms facing obsolescence risk may opt not to expand or to expand more slowly in response to a productivity shock. This is a typical result for adjustment cost models where irreversible costs are weighed against uncertain future revenues.

To test the relevance of this model, we use microdata from the US Census on manufacturing establishments from 1977 to 2018 and for firms in the nonfarm business sector from 1997 to 2018. We calculate total factor productivity for manufacturing establishments and labor productivity for firms in the nonfarm business sector. We use two different measures to capture technological rivalry, both based on the idea that the more that rivals perform R&D, the greater the risk rivalry poses to the focal firm. The first measure is based on the sum of rivals' R&D (the inverse hyperbolic sine of it); the second, developed in a previous paper (Ando et al. 2025), estimates the impact of technological rivalry by measuring the extent to which rivals' R&D affects own-firm R&D.

We then use these measures to test predictions of the model. First, using a linear probability model of inaction, we find that higher technological rivalry is associated with a greater likelihood that firms will not act—firms and establishments are less likely to change their employment after controlling for the magnitude of productivity shocks. Next, we run

[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.

employment growth regressions for both manufacturing establishments and for firms in the nonfarm business sector. We find that employment growth increases with productivity, but less so when technological rivalry is larger. That is, technological rivalry substantially reduces the growth response to productivity. At the sample mean, technological rivalry is associated with slower growth of manufacturing establishment of about 4 percent per annum and slower growth in the nonfarm business sector of 10-15 percent per annum. Finally, we apply our regression estimates to the data for the nonfarm business sector by calculating counterfactual employment growth without technological rivalry. We find that counterfactual employment growth shows little change in the slope of the employment response curve in Figure 2. And we find that with counterfactual employment, job reallocation rates only changed slightly between 1997 and 2018. While rising adjustment costs may have played a role in slowing job reallocation, it appears that technological rivalry may have exacerbated that role. In any case, rising technological rivalry can account for most of the decline in job reallocation rates.

The contribution of this paper is to highlight technological rivalry as an important factor affecting the reallocation of productive resources. We model the decisions of firms to expand using productive technology when hiring involves adjustment costs. We argue that technological rivalry affects firms' obsolescence risks. The model shows that productive firms may be less likely to expand and may expand less when they face greater technological rivalry. We then use measures of technological rivalry to test these predictions. We find evidence that technological rivalry affects the likelihood that productive firms will expand and the rate at which they choose to expand. Using data for the nonfarm business sector, we show that the magnitude of these effects can account for the decline in the response of firms to productivity shocks and for the decline in the rate of job reallocation.

Our findings suggest a somewhat different view from the literature on the relationship between competition and reallocation. 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. Our analysis suggests a more complicated relationship where technological rivalry, which is quite distinct from competition arising from lower regulatory or trade barriers, can slow reallocation. Similarly, technological rivalry complicates the relationship between industrial dynamism and the reallocation of productive resources. Technological rivalry is associated with several measures of industrial dynamism, including firm startup rates, exit rates, young age, and low industry concentration. But technological rivalry is also associated with lower job reallocation rates and a slower response to productivity shocks. While product market competition and some measures of industrial dynamism are related to reallocation, our analysis suggests that these relationships are more complicated. The pace of creative destruction is endogenous to some degree.

Several economists have proposed other candidates for factors leading to slower reallocation including rising adjustment costs, rising markups, and a changing output elasticity of labor (Hyatt and Spletzer 2013; Davis and Haltiwanger 2014; Decker et al. 2020; Cooper et al. 2024; Biondi et al. 2025). Whatever the role of these factors, our analysis suggests a prominent additional role for technological rivalry.

Technological rivalry figures in the industrial organization literature on innovation, mainly in the form of patent races.[2] But that literature focuses on the effect of rivalry on making innovations. Here, the focus is on what happens *after* innovations are made. The translation of innovations into aggregate productivity growth involves the growth of firms with productive innovations, the diffusion of those innovations to other firms, and the entry of new firms with productive innovations. This paper analyzes the growth of firms with innovations, but a similar analysis may apply to firm decisions regarding the adoption and licensing of innovations and the market entry of innovative firms.

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 2025; 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

Our model demonstrates how obsolescence affects firm 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 2025). Below we will

[2] Bloom et al. (2013) model the effect of rivals' R&D on firm own R&D incentives.

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 significant loss of 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, $F(\nu)$, such that $\ln A_{t+1} = \ln \overline{A} + \nu, \quad \mathbb{E}[\nu] = 0, \mathrm{var}[\nu] = \sigma^2$. 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

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

However, external developments can reduce the value of the profit stream with some probability, the obsolescence rate. 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

$$V(E_{t-1}, A_t) = \max_{E_t}[R(A_t, E_t) - WE_t - T \cdot \max(0, E_t - E_{t-1}) + B \cdot \mathbb{E}[V(E_t, A_{t+1})]] \quad (2)$$

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

It is convenient to designate log values in lower case, that is, $e = \ln E$, $a = \ln A$. To determine the optimal level e_t, we take the first order conditions maximizing the term in brackets. These first order equations differ depending on e_{t-1} and a_t. In the Appendix we show that these conditions create three solution zones distinguished by whether a_t is greater or less than boundary values $\underline{a}(e_{t-1})$ or $\overline{a}(e_{t-1})$:

1. In Zone I where $a_t < \underline{a}(e_{t-1})$, the optimal employment is $e_t^I = \frac{1}{1-\phi}(a_t + \ln \phi/w)$.
2. In Zone II where $\underline{a}(e_{t-1}) \leq a_t \leq \overline{a}(e_{t-1})$, $e_t^* = e_{t-1}$.
3. In Zone III where $a_t > \overline{a}(e_{t-1})$, $e_t^{III} = \frac{1}{1-\phi}\left(a_t + \ln \frac{\phi}{w+T(1-BP_{III}(e_t))}\right)$ where P_{III} is the a priori probability that the firm will receive a probability draw leading it to choose Zone III. This depends on the level of employment in the previous period,
$$P_{III}(e_{t-1}) \equiv 1 - F(\overline{a}(e_{t-1})), \;\; P_{III}(e_t) \equiv 1 - F(\overline{a}(e_t)).$$

Similarly,

$$P_I(e_{t-1}) \equiv F\big(\underline{a}(e_{t-1})\big), \qquad P_{II} \equiv 1 - P_I(e_{t-1}) - P_{III}(e_{t-1}) \quad (3)$$

These zones are shown in Figure 1. At low draws of a_t (Zone I), firms will reduce their employment relative to the previous period. As a_t grow larger, the level of log employment grows at a rate of $\frac{1}{1-\phi}$. This response occurs until $e_t^I = e_{t-1}$ at the boundary to Zone II. This is a zone of "inaction"—employment remains the same as in the previous period even as productivity grows. When log productivity reaches $\overline{a}(e_{t-1})$, Zone III is reached, and log employment again grows at a rate of $\frac{1}{1-\phi}$ as a_t increases.

This characterization of the solution allows us to identify two ways that obsolescence affects firm growth behavior. First, the boundary between Zones II and III changes, in turn, changing the a priori probabilities that the firm will choose each zone. Under a general condition, an increase in δ increases the upper boundary, $\frac{d\,\overline{a}(e_{t-1})}{d\,\delta} > 0$. The effect is to increase the size of the inaction zone, Zone II. Correspondingly the probabilities P_{II} and P_{III} change,

$$\frac{\partial P_I}{\partial \delta} = 0, \quad \frac{\partial P_{III}}{\partial \delta} < 0, \quad \frac{\partial P_{II}}{\partial \delta} > 0. \tag{4}$$

Below we empirically test whether greater obsolescence is associated with a higher probability of inaction.

Obsolescence also affects the level of employment within Zone III. We show that $\frac{d\,e_t^{III}}{d\,\delta} < 0$, reducing the intercept of the line e_t^{III} in the figure so that the level of employment is lower within Zone III.

We can use these insights to develop our empirical implementation. To show the contribution of obsolescence, we use the same data source as Decker et al. (2020) and we use a similar regression equation where we add terms to capture the obsolescence effect. Decker et al. obtain an equation for forward employment growth by taking the difference between years $t+1$ and t. Sweeping wages and constants into fixed effects, μ_{jt}, they get an equation of the form

$$\Delta e_{it} \equiv e_{it} - e_{it-1} = \theta_a a_{it} + \theta_T a_{it}\tau_{it} - e_{it-1} + \mu_{jt} + \epsilon_{it} \tag{5}$$

where τ_{it} is a trend measure that could capture a variety of changes such as changing labor adjustment costs or rising markups. Their regressions show that θ_T decreases over time, reducing the employment growth response to productivity.

In the Appendix we derive a similar equation using our model and approximating terms involving P_{II} and P_{III} as linear functions of δ

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

This specification nests both a trend term and two terms capturing obsolescence effects. We expect that $\theta_a > 0,\ \theta_x, \theta_\delta < 0$ where θ_x captures a reduced responsiveness and θ_δ represents a reduced level of growth. 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.

Obsolescence and R&D Demand

To implement regressions of equation (6), we need a functional form for δ. To do this, we assume that the obsolescence rate is an increasing function of rivals' R&D. The more that rivals invest in R&D, the greater the likelihood that they will develop innovations that replace the focal firm technology as in equation (2). As a first pass, $\delta = \gamma_0 + \gamma_1 \ln S$, where S is a measure of the R&D of other firms in the same industry. But we can formally derive measures of δ and of technological rivalry from the model above applied to the case where the firm develops its 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

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

Expressing this as an infinite sequence,

$$V(E_{t-1}, A_t)$$

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

As above, assuming $A_0 = 0$ for simplicity, $\mathbb{E}[A_{t+n}] \approx A_1 = I^{\beta}$ 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,

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

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).

Estimating technological rivalry and obsolescence

Following Ando et al. (2025), we use this equation to estimate technological rivalry and obsolescence. To do so, we use a flexible functional form to capture $\ln(r + \delta)$. Our assumption is that the obsolescence rate δ increases with rivals' R&D measured by the variable S. We will specify this measure below. Then $\delta_{it} = \delta(S_{it})$. We substitute a flexible form for $\ln(r + \delta)$ in equation (8),

$$\ln(r + \delta) = \ln r + \gamma \ln S + \mu \ln R \ln S\,. \tag{9}$$

The second term captures the rise in the obsolescence rate with rivals' R&D. The third term captures possible heterogeneity in the effect of rivals' R&D with firm size. Larger or older firms might face lower obsolescence rates because their consumers may face higher switching costs. 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. Then, the obsolescence rate will be lower.

With this form, we modify equation (8), sweeping the R&D price and discount rate into fixed effects to get an R&D demand equation

$$\ln I_{it} = \gamma_t + \gamma_J + \gamma_S \ln S_{it} + \gamma_x \ln S_{it} \cdot \ln R_{it} + \gamma_R \ln R_{it} + \epsilon_{it}, \tag{10}$$

where γ_t and γ_J denote the year and industry fixed effects.[3] Estimating this equation involves several important identification issues that we discuss below.

With estimates of the parameters, we can calculate the impact of rivals' R&D on focal firm R&D as a measure of technological rivalry,

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

In turn, we can invert equation (9) to obtain an estimate of endogenous obsolescence,

$$\hat{\delta}_{it} = r\left(e^{\hat{Z}_{it}} - 1\right) \approx r\hat{Z}_{it}. \tag{12}$$

where we use the first two terms of a Taylor series expansion to get the approximation. Using this, equation (6) can be reparametrized as

$$\Delta e_{it} = \theta_a a_{it} + \theta_\tau a_{it}\tau_{it} + \theta_x a_{it}\hat{Z}_{it} + \theta_\delta \hat{Z}_{it} - e_{it-1} + \mu_{jt} + \epsilon_{it}. \tag{13}$$

[3] We allow γ_R to differ from 1 because a substantial empirical literature finds scale effects in the productivity of R&D (W. M. Cohen and Klepper 1996; W. M. Cohen 2010).

We estimate this equation below, using multi-factor productivity for the manufacturing sector and revenue labor productivity for the non-farm business sector. We also use the simpler measure of technological rivalry, just $\ln S_{it}$, effectively dropping the smaller second term of equation (11).

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. Note that our model uses last year's end-of-year employment as a key variable. To be consistent with this growth measure, we use current year March employment in lieu of employment from the previous December.

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.

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

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 (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

[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).

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. 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.

Rivals' R&D. Only *some* firms are likely to develop new technology that makes focal firm knowledge obsolete; we don't expect software firms to obsolesce the knowledge of steel producers. We measure the effects of rivalry only within industries, broadly defined. As a baseline specification, let S capture the sum of R&D expenditures by other firms in the same primary industry; for firm *i* in industry *J* let $S_{it} \equiv \sum_{\substack{j \neq i \\ j \in J}} I_{jt}$. We use 6-digit NAICS industries.

[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.

As a robustness check, Bessen and Wang (2025) construct an alternative measure of rivals' R&D constructed as an distance weighted sum of R&D expenditures across multiple industries. That paper found little difference using the alternative measure. In any case, using 6-digit industries we surely miss some firms that might be a source of obsolescence, and we include some firms that are not. To the extent that we mis-measure industries, our coefficients on rivals' R&D will be attenuated. Furthermore, rather than use a capital stock for rivals' investment, we use lagged investment expenditure. Because of the limited longitudinal dimension of our data, calculating capital stocks would severely reduce our sample. While the lagged expenditure also reduces our sample, the reduction is less. We check the robustness of our results to sample selection bias using inverse propensity weights (not reported), finding broadly similar results. Finally, because of incomplete sampling, some of our industry measures of R&D are quite small; to avoid extreme values of small logarithms, we use inverse hyperbolic sine (asinh), instead of simple logarithms, substituting $\text{asinh}\left(\sum_{\substack{j\neq i \\ j\in J}} I_{jt-1}\right)$ for $\ln S_{it}$ in equation (10).

4. Empirical Findings

Technological Rivalry

We seek to test the role of technological rivalry using regressions of equation (13). To estimate technological rivalry, $\hat{Z}$, we use equation (10), which relates rivals' R&D to own-firm R&D under the assumption that firms reduce their R&D investment when faced with obsolescence risk arising from rivals' R&D. In some growth regressions, we also use a simpler proxy measure, the inverse hyperbolic sine of rivals' R&D.

Several identification challenges to measuring $\hat{Z}$ this way: 1) Knowledge spillovers from rivals' R&D might affect the focal firm aside from obsolescence risk. Looking at

equation (8), rivals' R&D could affect focal firm revenue or the output elasticity of R&D, β. 2) Focal firms and rivals may both experience common unobserved productivity or demand shocks. Then rivals' R&D will be correlated with the error term, biasing $\hat{Z}$ towards zero. 3) Obsolescence occurs through product market competition, but rival firms' R&D might be correlated with competition conditions. In this case, our measure of rivals' R&D might proxy for competition conditions, biasing estimates of $\hat{Z}$. 4) Rivals' R&D might affect input markets rather than product markets, raising the cost of scientists and engineers. We briefly consider these confounding influences; a more complete discussion can be found in our related paper (Ando et al. 2025).

Table 1 shows baseline regressions for each of the four periods. 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. Panel A shows the simple regression with just the rivals' R&D term on the right-hand side with industry and year fixed effects. 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. The coefficients are negative, quite large, and their magnitudes are larger in later periods. Note that we are careful not to use industry-by-year fixed effects because our measure of rivals' R&D is constructed as a leave-one-out variable that is implicitly related to the dependent variable. With industry-by-year fixed effects, this could mechanically generate a spurious negative regression coefficient. However, with separate industry and year fixed effects we show in the Appendix that any the bias arising from the construction of S is small.

One identification issue is the direct effect of rivals' R&D on the focal firm, most notably via knowledge spillovers. Spillovers could affect the output elasticity of R&D, or they could directly affect firm revenue. In the related paper, we find evidence that rivals'

R&D is associated with a modestly larger output elasticity, β. But this complementary effect is small, implying that, at worst, our estimates of $\hat{Z}$ will be slightly understated. Spillovers might also directly affect firm revenue.[7] But in this case, the spillover effect is implicitly captured in the revenue variable that is included in the right-hand side of equation (10). To incorporate these direct effects, Panel B adds terms involving log real revenues and an interaction with $\text{asinh}\, S$. 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.[8] The bottom row of the table reports estimates of the technological rivalry measure using equation (11). 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.

Our estimates of $\hat{Z}$ may be subject to omitted variable bias if both the focal firm and its rivals are subject to common productivity or demand shocks arising, say, from technological opportunities or changing demand. Common shocks would tend to make Z understated. Another problem is that firm revenues are endogenous—firms may want to invest more in R&D to increase their size and hence reduce customer switching. In the Appendix (Tables A1-3), we present regressions where we instrument rivals' R&D using R&D tax cost. To instrument rivals' R&D, we follow Bloom et al. (2013) and use Federal and state tax costs of R&D to provide a plausibly exogenous instrument. The exclusion

[7] Griliches (1979) suggests a Cobb-Douglas form similar to, in our notation, $R = A_0 S^{\gamma} X^{\alpha} K^{\beta}$.

[8] Bessen and Wang (2025) run similar regressions with different sales measures and find similar results.

restriction requires that R&D tax costs should not affect focal firm R&D except via the effect of tax costs on rivals' R&D.[9] Thus, for example, state level tax costs should not affect product market competition in national industries; we find that industry competition measures (HHI, CR4, and markups) are, in fact, uncorrelated with R&D tax costs [TK]. We also instrument firm revenue, 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.

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.[10] 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

[9] And we further strengthen the exclusion assumption by only including rival R&D from other states in building the instrument.

[10] 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 et al. 2023).

R&D and is more than just a proxy for rivals' market share, etc. We also tested specifications with controls for a wide variety of IO competition concerns.[11]

Another confounding influence might arise if rivals' R&D increases the competition for R&D inputs, mainly scientists and engineers, rather than acting via product market competition. In Ando et al. (2025) we note that the wage premiums of these occupations have not risen and we exclude a role for labor adjustment costs and monopsony. In the Appendix, we perform several additional robustness checks. 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.

Our measure of technological rivalry thus appears to be robust to several confounding concerns, although it likely suffers some measurement error. Moderate measurement error may attenuate coefficient estimates in the employment growth regressions below, but these estimates are nevertheless substantial. Moreover, our measure of technological rivalry appears to capture some basic aspect of technological rivalry; it 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

[11] 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).

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).

Inaction

We first test whether technological rivalry affects the likelihood that a firm chooses not to make a significant change in employment. Table 3 [TK] show results from a linear probability model of an indicator of inaction; the dependent variable is 1 if firm or establishment growth falls within a narrow range around zero and is otherwise 0. The first three columns show regressions for manufacturing establishments with three different test ranges ($\pm.01, \pm.05, \pm.10$). The right-hand side includes the asinh of rivals' R&D and controls for the absolute value of productivity change, and industry and year fixed effects. The fourth column shows the regression for firms in the nonfarm business sector for just the test range of $\pm.01$, using the estimated value of $\hat{Z}$. [TK the results await disclosure from Census]. The bottom rows of the table report the implied magnitude of the effect at the sample mean and the overall share of firms classified as inactive in any year.

Firm Growth

Next, we explore the relationship between establishment growth and multi-factor productivity in the manufacturing sector in Table 4. Column 1 shows the regression for

equation (13).[12] 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 share of firm employment outside of manufacturing.[13] 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 5 expands the analysis to non-manufacturing industries; this is important because some of the strongest rivalry levels are outside manufacturing (see Appendix Table

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[12] Note that the firm anticipates a_{t+1} from the TFP achieved in year *t*. Because Table 1 estimates $\hat{Z}_{it}$ for the entire non-farm business sector, we do not use these estimates for analyzing the manufacturing sector specifically. We use $\operatorname{asinh} S_{it-1}$ in lieu of $\hat{Z}_{it} = -(\hat{\gamma}_S \cdot \operatorname{asinh} S_{it-1} + \hat{\gamma}_x \cdot \operatorname{asinh} S_{it-1} \cdot \ln R_{it})$. The second term of $\hat{Z}_{it}$ 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.

[13] 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.

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), not reporting the display of coefficients for log employment. Standard errors are clustered by industry. The values of $\hat{Z}_{it}$ are calculated from the regressions in Table 1.

Columns 1 and 2 of Table 5 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 are negative and significant.[14] 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

[14] 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.

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 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

$$D_{it} = \hat{\theta}_{\delta} Z_{it} + \hat{\theta}_{x} Z_{it} a_{it}. \tag{15}$$

Table 6 shows the sample mean value for two time periods, 1997-2007 and 2008-2018 using coefficient values from Table 5, 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 also calculate the effect of counterfactual growth on 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.[15] We calculate the counterfactual job reallocation as:

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

Table 6 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

Our model and empirical findings suggest that the relationship between technological rivalry and productivity growth is two-sided. On the one hand, technological rivalry is a central component of Schumpeterian creative destruction, as rival firms replace incumbent technologies with new, more productive ones. But technological rivalry also

[15] The actual calculation includes inverse propensity weights.

raises obsolescence risk, causing firms to slow their implementation of new technologies. We show that firms faced with greater rivalry are less likely to expand after a positive productivity shock and, on average, these firms expand more slowly. The effects on firm and establishment growth rates are substantial, and in aggregate data rising technological rivalry can account for most of the decline in firm response to productivity shocks and most of the decline in job reallocation rates.

Of course, other factors such as adjustment costs may also affect reallocation, but our findings suggest that the role of technological rivalry should not be ignored and they highlight the importance of further research to understand what factors affect the intensity of technological rivalry. The large increase in business R&D surely play a role, but the nature of rivalry may also be changing. And these changes may affect other aspects of the way new technologies translate into productivity growth. In effect, technological rivalry affects the time horizons that firms use to make decisions about expansion. Further research can tell whether similarly shorter time horizons also affect firm decisions to enter markets or to adopt or license new technologies.

References

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica* 83 (6): 2411–51.

Alfaro, Laura, and Anusha Chari. 2014. "Deregulation, Misallocation, and Size: Evidence from India." *The Journal of Law and Economics* 57 (4): 897–936.

Alfaro, Laura, and Maggie X. Chen. 2018. "Selection and Market Reallocation: Productivity Gains from Multinational Production." *American Economic Journal: Economic Policy* 10 (2): 1–38.

Ando, Yoshiki, James Bessen, and Xiupeng Wang. 2025. *The Rising Returns to R&D: Ideas Are Not Getting Harder to Find*. TPRI Working Paper. https://ssrn.com/abstract=5242171.

Arnold, Jens Matthias, Giuseppe Nicoletti, and Stefano Scarpetta. 2011. "Regulation, Resource Reallocation and Productivity Growth." *European Investment Bank Papers* 16 (1): 90–115.

Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen. 2020. "The Fall of the Labor Share and the Rise of Superstar Firms." *The Quarterly Journal of Economics* 135 (2): 645–709.

Backus, Matthew. 2020. "Why Is Productivity Correlated with Competition?" *Econometrica* 88 (6): 2415–44.

Baqaee, David Rezza, and Emmanuel Farhi. 2020. "Productivity and Misallocation in General Equilibrium." *The Quarterly Journal of Economics* 135 (1): 105–63.

Barth, Erling, James C. Davis, Holden A. Diethorn, Gerald R. Marschke, and Andrew Wang. 2023. "Worker Mobility, R&D Human Capital, and Firm Productivity." *Working Paper*.

Bentolila, Samuel, and Giuseppe Bertola. 1990. "Firing Costs and Labour Demand: How Bad Is Eurosclerosis?" *The Review of Economic Studies* 57 (3): 381–402.

Berry, Steven, Martin Gaynor, and Fiona Scott Morton. 2019. "Do Increasing Markups Matter? Lessons from Empirical Industrial Organization." *Journal of Economic Perspectives* 33 (3): 44–68.

Bessen, James, and Xiupeng Wang. 2025. "The Intangible Divide: Why Do so Few Firms Invest in Innovation?" *Center for Economic Studies Working Papers*, no. CES-25-15.

Biondi, Filippo, Sergio Inferrera, Matthias Mertens, and Javier Miranda. 2025. *Declining Job Reallocation in Europe: The Role of Shocks, Market Power, and Technology*. IWH Discussion Papers.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica* 81 (4): 1347–93.

Cohen, Assa. 2023. "A Crosswalk from the Business R&D and Innovation Survey (BRDIS) and the Survey of Industrial Research and Development (SIRD) to the Longitudinal Business Database (LBD)." *CES Technical Notes Series*, Center for Economic Studies, US Census.

Cooper, Russell, John C. Haltiwanger, and Jonathan Willis. 2024. *Declining Responsiveness at the Establishment Level: Sources and Productivity Implications*. National Bureau of Economic Research.

Cunningham, Cindy, Lucia Foster, Cheryl Grim, et al. 2023. "Dispersion in Dispersion: Measuring Establishment-Level Differences in Productivity." *Review of Income and Wealth* 69 (4): 999–1032.

Davis, Steven J., and John Haltiwanger. 2014. *Labor Market Fluidity and Economic Performance*. National Bureau of Economic Research.

Davis, Steven J., John Haltiwanger, and Scott Schuh. 1996. "Small Business and Job Creation: Dissecting the Myth and Reassessing the Facts." *Small Business Economics* 8: 297–315.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The Rise of Market Power and the Macroeconomic Implications." *The Quarterly Journal of Economics* 135 (2): 561–644.

Decker, Ryan A., John C. Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2020. "Changing Business Dynamism and Productivity: Shocks vs. Responsiveness." *American Economic Review* 110 (12): 3952–2990.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2016. "Declining Business Dynamism: What We Know and the Way Forward." *American Economic Review* 106 (5): 203–7.

Decker, Ryan A., John Haltiwanger, Ron S. Jarmin, and Javier Miranda. 2017. "Declining Dynamism, Allocative Efficiency, and the Productivity Slowdown." *American Economic Review* 107 (5): 322–26.

Foster, Lucia, John C. Haltiwanger, and Cornell John Krizan. 2001. "Aggregate Productivity Growth: Lessons from Microeconomic Evidence." In *New Developments in Productivity Analysis*. University of Chicago Press.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review* 98 (1): 394–425.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2016. "The Slow Growth of New Plants: Learning about Demand?" *Economica* 83 (329): 91–129.

Gao, Wei, and Matthias Kehrig. 2017. "Returns to Scale, Productivity and Competition: Empirical Evidence from US Manufacturing and Construction Establishments." *Productivity and Competition: Empirical Evidence from US Manufacturing and Construction Establishments (May 1, 2017)*.

Gilbert, Richard. 2006. "Looking for Mr. Schumpeter: Where Are We in the Competition–Innovation Debate?" *Innovation Policy and the Economy* 6: 159–215.

Griliches, Zvi. 1979. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *The Bell Journal of Economics*, 92–116.

Haltiwanger, John, Ron Jarmin, Robert Kulick, Javier Miranda, and Veronika Penciakova. 2019. *Augmenting the LBD with Firm-Level Revenue*. CES Technical Notes.

Haltiwanger, John, Ron S. Jarmin, Robert Kulick, and Javier Miranda. 2016. "High Growth Young Firms: Contribution to Job, Output, and Productivity Growth." In *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*. University of Chicago Press. https://www.nber.org/books-and-chapters/measuring-entrepreneurial-businesses-current-knowledge-and-challenges/high-growth-young-firms-contribution-job-output-and-productivity-growth.

Hopenhayn, Hugo, and Richard Rogerson. 1993. "Job Turnover and Policy Evaluation: A General Equilibrium Analysis." *Journal of Political Economy* 101 (5): 915–38.

Huang, Ning, and Erwin Diewert. 2011. "Estimation of R&D Depreciation Rates: A Suggested Methodology and Preliminary Application." *Canadian Journal of Economics/Revue Canadienne d'économique* 44 (2): 387–412.

Hyatt, Henry R., and James R. Spletzer. 2013. "The Recent Decline in Employment Dynamics." *IZA Journal of Labor Economics* 2: 1–21.

Klemperer, Paul. 1995. "Competition When Consumers Have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade." *The Review of Economic Studies* 62 (4): 515–39.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies* 70 (2): 317–41.

Li, Wendy CY, and Bronwyn H. Hall. 2020. "Depreciation of Business R&D Capital." *Review of Income and Wealth* 66 (1): 161–80.

Lucking, Brian, Nicholas Bloom, and John Van Reenen. 2019. "Have R&D Spillovers Declined in the 21st Century?" *Fiscal Studies* 40 (4): 561–90.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies* 60 (3): 531–42.

Mead, Charles Ian and others. 2007. "R&D Depreciation Rates in the 2007 R&D Satellite Account." *Bureau of Economic Analysis/National Science Foundation*.

Olley, G. Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6): 1263–97.

Raval, Devesh. 2023a. "A Flexible Cost Share Approach to Markup Estimation." *Economics Letters* 230 (September): 111262. https://doi.org/10.1016/j.econlet.2023.111262.

Raval, Devesh. 2023b. "Testing the Production Approach to Markup Estimation." *Review of Economic Studies* 90 (5): 2592–611.

Shapiro, Carl. 2011. "Competition and Innovation: Did Arrow Hit the Bull's Eye?" In *The Rate and Direction of Inventive Activity Revisited*. University of Chicago Press.

Shapiro, Carl, and Ali Yurukoglu. 2026. "Trends in Competition in the United States: What Does the Evidence Show?" *Journal of Political Economy Microeconomics* 4 (1): 000–000.

Sivadasan, Jagadeesh. 2009. "Barriers to Competition and Productivity: Evidence from India." *The BE Journal of Economic Analysis & Policy* 9 (1).

Wilson, Daniel J. 2009. "Beggar Thy Neighbor? The in-State, out-of-State, and Aggregate Effects of R&D Tax Credits." *The Review of Economics and Statistics* 91 (2): 431–36.

Xu, Rui, and Kaiji Gong. 2017. *Does Import Competition Induce R&D Reallocation? Evidence from the US*. International Monetary Fund.

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 ($\overline{Z_{it}}$)	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 (Z)	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. Likelihood of Inaction [data awaiting Census release]

	(1)	(2)	(3)	(4)
Dependent variable: Probability Growth Falls within Range				
Range	+/- .01	+/- .05	+/- .10	+/- .01
Sample	Manufacturing establishments	Manufacturing establishments	Manufacturing establishments	Nonfarm business firms
Rivals' R&D ($\text{asinh}\, S$)				
Technological rivalry (Z)				
|Productivity growth|				
Adjusted R^2				
N				
Effect at sample mean				
Inaction share				

Note: Regressions include detailed industry and year fixed effects. Standard errors are clustered by detailed industry

Table 4. 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 ($\text{asinh}\, S$)	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		

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 $\text{asinh}\, S_{it-1}$. 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 taken at the sample means. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12510).

Table 5. Firm Growth and Technological Rivalry, Nonfarm 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 (Z) x log LP	-0.003***				
	(0.001)				
Rival impact IV x log LP		-0.003***			
		(0.001)			
Imputed rival impact (Z)			-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 6. Aggregate Job Reallocation

Period	1997-2007	2008-2018
Mean rival impact (Z)	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 (Z) 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).

Figures

Figure 1. Solution Zones

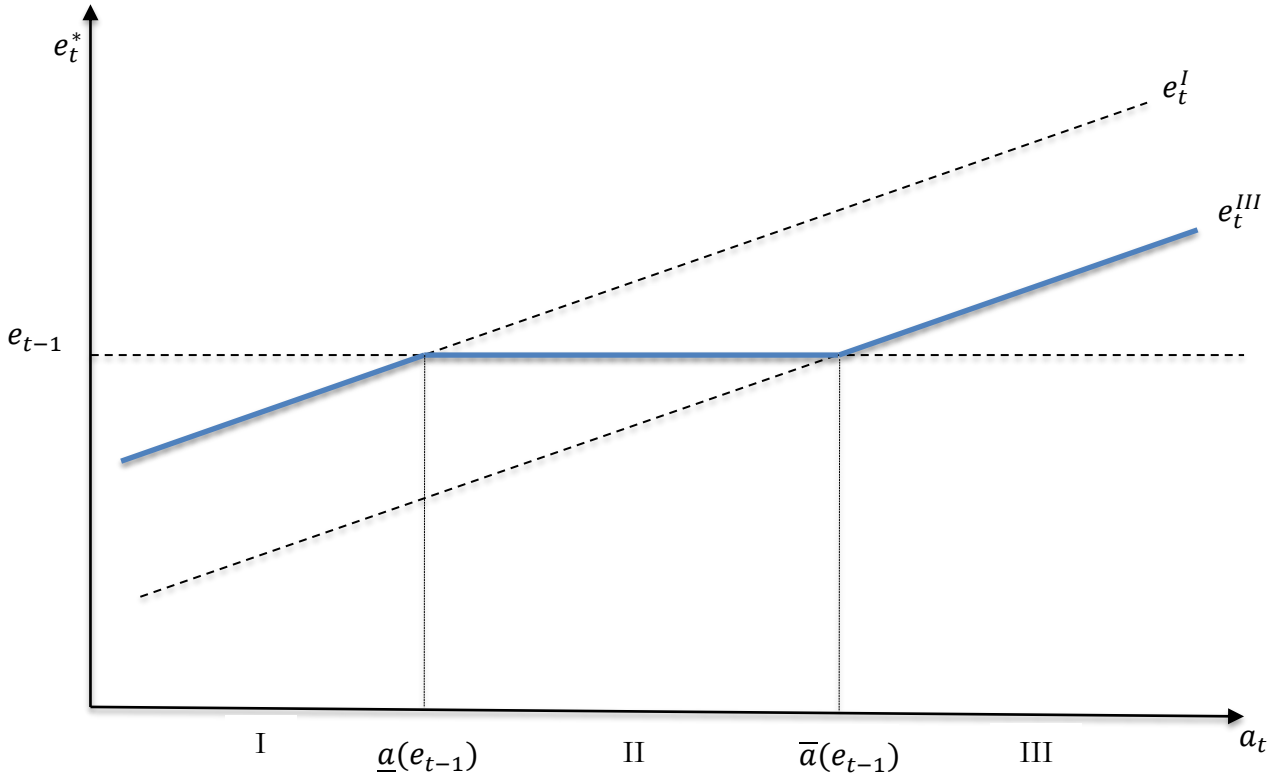
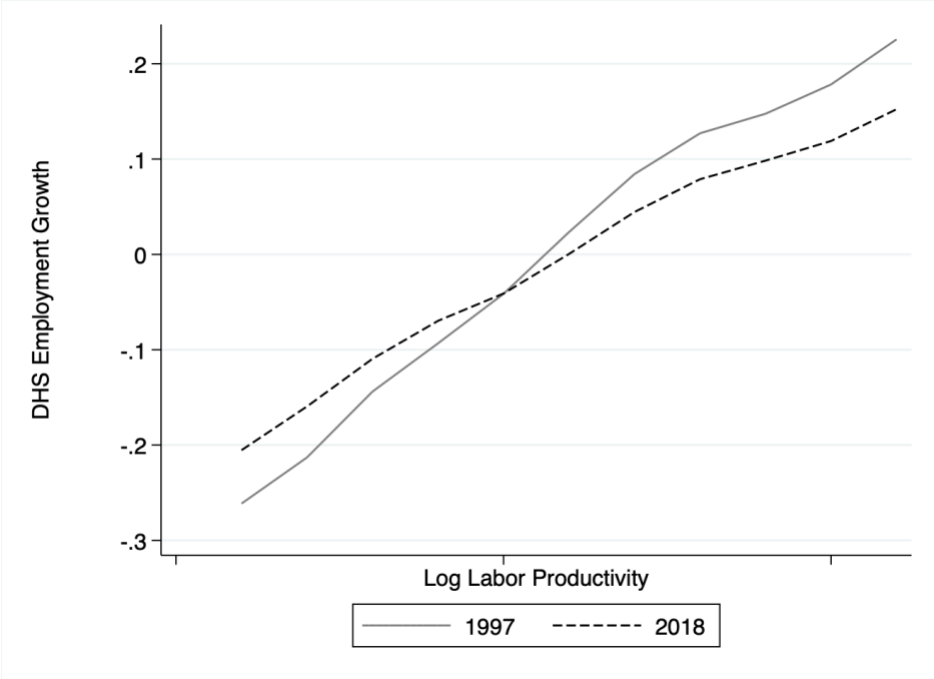
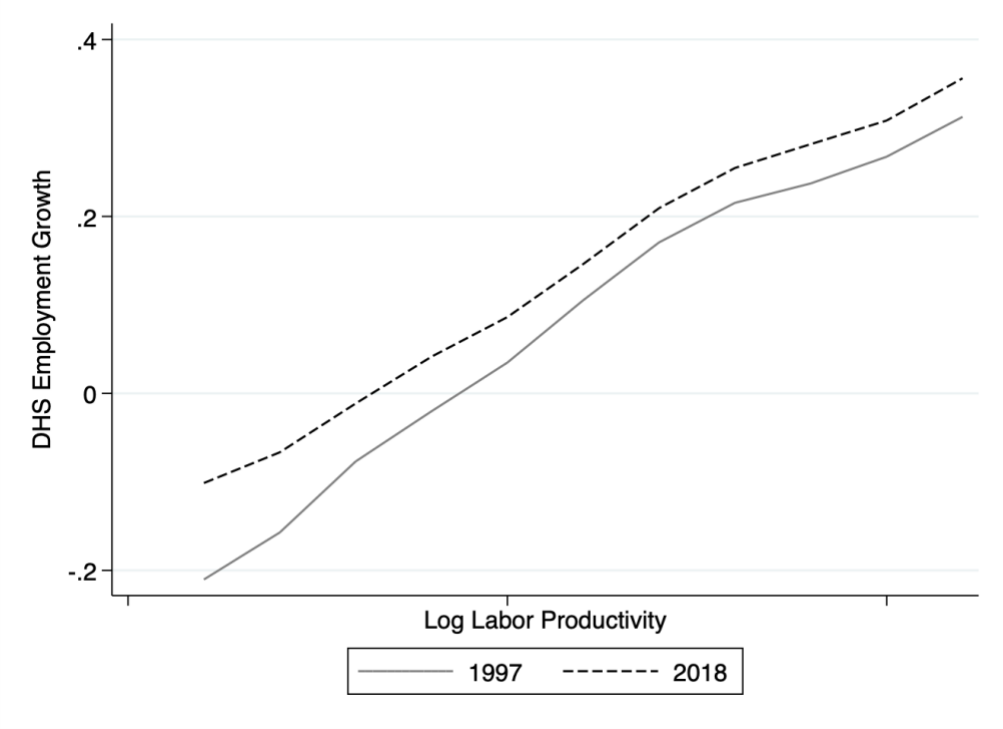


Figure 2. Firm Growth and Productivity

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 A1 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 ($\overline{Z}_{it}$)		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 excluding rivals from same state as focal firm 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

The leave-one-out construction makes the rivalry measure implicitly related to the dependent variable, $S_{it} \equiv \sum_{\substack{j \neq i \\ j \in J}} I_{jt} = \sum_{j \in J} I_{jt} - I_{it}$. With industry-by-year fixed effects, $\sum_{j \in J} I_{jt}$ will be absorbed into the fixed effect, making S_{it} related to the negative of the dependent variable, mechanically generating a spurious negative regression coefficient.[16] However, with separate industry and year fixed effects and sufficient year-to-year variation in R&D, this effect is limited.

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,

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

[16] This is similar to Manski's "reflection problem" (1993).

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

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

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

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, $\overline{\log I_i} = \frac{1}{T}\sum_t \log I_{it}$. We can show that[17]

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

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 $var\left(\overline{\frac{I_i}{T_i}}\right)/var(S_{it-1})$ 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

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

	$-\frac{cov\left(\overline{\log I_\iota}, \frac{I_{it-1}}{T_{it-1}}\right)}{var(S_{it})}$	$\frac{\overline{var\left(\frac{I_\iota}{T_\iota}\right)}}{var(S_{it})}$
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 5. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

3. Bellman Solution Employment Growth Zones

In Zone I, $E_t < E_{t-1}$, so the first order condition, taking the derivative of the bracketed term in equation (1), is

$$\phi A_t E_t^{\phi-1} - W = 0.$$

Taking logs, this solves to

$$e_t^I = \frac{1}{1-\phi}\left[a_t + \ln\left(\frac{\phi}{W}\right)\right]. \tag{B1}$$

The boundary between Zones I and II occurs when $e_t^I = e_{t-1}$ so that

$$\underline{a}(e_{t-1}) = (1-\phi)e_{t-1} - \ln\left(\frac{\phi}{W}\right). \tag{B2}$$

The characterization of Zone III is a bit more complicated because we need to determine how current employment affects the continuation value. Let $\overline{a}$ denote the boundary between Zones II and III. In the inaction region, the firm is locally indifferent to changing employment. As a result, by the envelope theorem, the indirect effect of current employment on the continuation value through next period's optimal employment choice is zero to first order. Using this, we obtain:

$$\frac{\partial\, \mathbb{E}[V(E_t, A_{t+1})]}{\partial\, E_t} = -T\frac{\partial}{\partial\, E_t}\int_{\overline{a}}^{\infty} F'(a)(E_{t+1}(a) - E_t)\, da$$

$$= T\int_{\overline{a}}^{\infty} F'(a)da + T(E_{t+1}(\overline{a}) - E_t)F'\left(\overline{a}(E_t)\right)\frac{\partial\, \overline{a}(E_t)}{\partial\, E_t}$$

$$= TP_{III}(e_t), \qquad P_{III}(e_t) \equiv 1 - F\big(\overline{a}(e_t)\big)$$

where the second term in the second row drops out because, by definition, at the boundary $E_{t+1}(\overline{a}) = E_t$. Then the first order condition becomes

$$\phi A_t E_t^{\phi-1} - W - T + BTP_{III}(e_t) = 0$$

so that e_t^{III} solves

$$e_t = \frac{1}{1-\phi}\left(a_t + \ln\frac{\phi}{W + T\big(1 - BP_{III}(e_t)\big)}\right) \qquad (B3)$$

and $\overline{a}(e_{t-1})$ solves

$$a_t = (1-\phi)e_{t-1} - \ln\frac{\phi}{W + T\left(1 - BP_{III}\big(e_t(a_t)\big)\right)}. \qquad (B4)$$

These two equations may require numerical methods to solve.

Equations (B3) and (B4) are useful for analyzing the effect of changing obsolescence on the solution zones. Start by taking the implicit derivative $\frac{d\,\overline{a}}{d\,B}$ using (B4),

$$\frac{d\,\overline{a}}{d\,\delta} = \frac{d\,\overline{a}}{d\,B}\frac{-1}{1+r} = \frac{TP_{III}}{T + W - BT\big(P_{III} + F'(\overline{a})\big)}\frac{1}{1+r} > 0 \;\; \forall\, P_{III} < \overline{P} \qquad (B5)$$

where $\overline{P}$ is defined such that $\overline{P} + F'\left(F^{-1}\big(1-\overline{P}\big)\right) = 1$. This condition, although stronger than necessary, is sufficient to ensure that $\frac{d\,\overline{a}}{d\,\delta} > 0$ and is readily met by standard distribution functions. For instance, for a normal distribution, $\overline{P} \approx .62$. In our data, $P_{III} \approx .25$, so this condition is easily met. In this case, rising obsolescence increases the boundary between the inaction zone and Zone III.

Using this result, we can also determine the effect of obsolescence on the level of employment in Zone III using equation (B4).

$$\frac{d\, e_t^{III}}{d\, \delta} = \frac{\partial e_t^{III}}{\partial B}\frac{d\, B}{d\delta} + \frac{\partial e_t^{III}}{\partial \overline{a}}\frac{d\overline{a}}{d\delta} < 0. \qquad (B6)$$

From the previous results, $\frac{d\, B}{d\delta} < 0$ and $\frac{d\overline{a}}{d\delta} > 0$ are already known. In equation (B3), $e_t^{III}$is increasing in B, as a higher continuation value implies a larger expected future benefit of hiring today if the firm is in Zone III. In contrast, $e_t^{III}$is decreasing in $\overline{a}$, as a higher threshold reduces the probability of remaining in Zone III in the next period, lowering the expected payoff of today's hiring. Combining these effects, we obtain $\frac{d\, e_t^{III}}{d\, \delta} < 0$, and obsolescence decreases the employment level in Zone III.

The result in (B5) informs how the probabilities $P_j, j = I, II, III$ change with obsolescence.

$$\frac{\partial P_I}{\partial \delta} = F' \frac{\partial \underline{a}}{\partial \delta} = 0, \quad \frac{\partial P_{III}}{\partial \delta} = -F' \frac{\partial \overline{a}}{\partial \delta} < 0, \quad \frac{\partial P_{II}}{\partial \delta} = -\frac{\partial P_I}{\partial \delta} - \frac{\partial P_{III}}{\partial \delta} > 0. \qquad (B7)$$

We can use these findings to derive a regression equation. Using (B1) and (B3), we can write the expected employment level as

$$\begin{aligned}\mathbb{E}[e_t] &= \frac{P_I}{1-\phi}(a_t + \ln \phi/W) + P_{II} e_{t-1} + \frac{P_{III}}{1-\phi}(a_t + \ln \phi/W + Z) \\ &= \frac{1-P_{II}}{1-\phi}(a_t + \ln \phi/W) + P_{II} e_{t-1} + \frac{P_{III} Z}{1-\phi}, \quad Z \equiv \ln\left(1 + \frac{T}{W}(1 - BP_{III})\right).\end{aligned}$$

Approximating P_{II} and $P_{III}Z$ with linear functions of δ, putting wages and other factors into fixed effects, and subtracting e_{t-1} we obtain a growth regression equation

$$\Delta e_{it} = e_{it} - e_{it-1} = \theta_a a_{it} + \theta_x a_{it} \cdot \delta_{it} + \theta_\delta \delta_{it} - e_{it-1} + \mu_{jt} + \epsilon_{it}. \qquad (B8)$$

where μ_{jt} captures fixed effects and ϵ_{it} is an error term. This regression equation yields (6) in the text with the addition of a trend term. We suppress a possible term δe_{t-1} arising from

$P_{II}e_{t-1}$ because this term may exaggerate the negative effect of obsolescence; this is because of possible division bias between mismeasured e_{t-1} and the dependent variable.

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 (Z_{it})
Mean industry Z	1.527***
	(0.0790)
Mean industry Z 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).