The Rising Returns to R&D:

Ideas are not getting harder to find

By Yoshiki Ando (Singapore Management University, TPRI), James Bessen (BU, TPRI), and Xiupeng Wang (Northeastern, TPRI)

December 2025.

Abstract:
R&D investment has grown robustly, yet aggregate productivity growth has stagnated. Is this because "ideas are getting harder to find"? This paper uses micro-data from the US Census Bureau to explore the relationship between R&D and productivity in the manufacturing sector from 1976 to 2018. We find that both the elasticity of output (or TFP) with respect to R&D and the marginal returns to R&D have risen sharply, implying more effective R&D. But this means that rivals' R&D has also gotten more effective. Using a novel estimation approach, we find evidence of sharply rising technological rivalry and obsolescence. In the data, productivity growth rises with growth in the R&D capital stock, not with the level of R&D spending per se (as in Romer 1990). Higher obsolescence slows the accumulation of R&D capital, reducing the contribution of R&D to productivity growth and shortening the lives of innovations.

JEL Codes: O32, O33, L10
Keywords: R&D, innovation, productivity, obsolescence

Thanks to Holden Diethorn for providing data on tax costs. Thanks to comments from participants at the BU Applied Micro seminar, TPRI seminar, the IIOC, MIT Futuretech, Fairfield University, Univ. of Nottingham, the Chinese Economists Society, FSRDC Annual Conference, Harvard Seminar in the Economics of Science and Engineering, University of Berne, National University of Singapore, Singapore Management University, CTIER, and CIGS Macro Conference. Also, specific thanks to Jordi Jaumandreu, Mark Rysman, Mert Demirer, and Matt Mertens. This work was supported in part through grants from the Smith Richardson Foundation and the Alfred P. Sloan Foundation (Grant #2023-21111). Any views expressed are those of the authors and not those of the U.S. Census Bureau. The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743, CBDRB-FY25-P2735-R12155, CBDRB-FY25-P2735-R12336, CBDRB-FY25-P2735-R12452, and CBDRB-FY26-P2735-R12846).

1. Introduction

In Romer's 1990 growth model, the productivity growth rate is proportional to the number of researchers. R&D (research and development) generates new, non-rivalrous "ideas" that are shared across the economy, multiplying output. Thus, it is encouraging that R&D has grown rapidly both in absolute and relative terms; business R&D in the US has more than doubled since 1980 relative to business value added (see Figure 1; the rise in total R&D to GDP is similar). But economists have noted that despite this increase, productivity growth has been stagnant or declining. The ratio of patents to R&D declined, suggesting that somehow R&D was losing its effectiveness at generating new ideas (Kortum 1993; Jones 1995; Griliches 2009). In a similar vein, Robert Gordon (2017) argues that recent information technology innovations do not bring the kind of productivity growth that arose from the major technologies of the 19th and early 20th centuries. Bloom et al. (2020; but see critique by Alston and Pardey 2022) suggest that the reason for this breakdown may be that R&D has become less effective, that "ideas are getting harder to find." Motivated by Romer's equation relating productivity growth to R&D, they propose measuring research productivity as the ratio of productivity growth to real R&D. They apply this measure to both the macroeconomy and to individual firms, finding declines of 5 percent per year for the former and 8-10 percent per year for firms.

This trend seems ominous, but it is not clear that the ratio of productivity growth to R&D is the best measure of R&D productivity. Below we present evidence that challenges Romer's equation underlying this metric. But more basically, many factors other than R&D affect the level of productivity (Syverson 2011), influencing the ratio of average productivity growth to R&D. The *marginal* effect of R&D on productivity at the firm level should provide a better measure that can distinguish research effectiveness from other influences. Fortunately, a large empirical literature based on the knowledge production function, which we describe below, has developed methods for estimating these marginal effects (Griliches 1979; Hall et al. 2010).

This paper applies these well-established methods to micro-data from the US Census for the US manufacturing sector. We extend the literature by using a comprehensive sample of R&D-performing firms, including many small firms, and we study a relatively long period, from 1976 to 2018. We focus on manufacturing because revenue productivity is reasonably

well-measured in this sector.[1] Over a variety of estimations, including estimates with instrumented R&D, we find a consistent pattern: the output elasticity of R&D has increased substantially over the last four decades. At the margin, it appears that R&D has become substantially *more effective* at generating productivity-enhancing ideas, not less. All else equal, higher output elasticity should raise the ratio of R&D to output, as in Figure 1.

But if firms' R&D is more effective, why hasn't that translated into faster productivity growth? The knowledge production function model used in the empirical work provides a possible explanation. In this model, the contribution of R&D to productivity growth is the output elasticity of R&D times the growth of the "knowledge stock," calculated from the stream of "depreciated" R&D investments using the perpetual inventory method. While higher output elasticity should raise productivity growth, sluggish growth in the R&D stock might slow growth. And the growth of the R&D stock slows when the rate of obsolescence rises.

This paper considers the possibility that rising technological rivalry has increased the rate of obsolescence, reducing the contribution of R&D to productivity growth. Indeed, the rising effectiveness of R&D may itself promote greater technological rivalry: as individual firms become more innovative, so, too, do their rivals, raising the risk that rivals' innovations obsolesce a firm's knowledge stock.

A variety of casual evidence suggests that technological rivalry is indeed rising, accompanied by shorter product lives that are equivalent to faster obsolescence. Consider microprocessors. During the 1990s, Advanced Micro Devices became more competitive with Intel, the market leader, by introducing new, less expensive semiconductors. Intel responded by accelerating the introduction of its own new models. Over time, product introductions happened more frequently and product lives shortened (Aizcorbe 2005). This pattern is seen not only in microprocessors, but in other semiconductors and electronic components generally where product life cycles have declined by 60% (Hochbaum et al. 2011 Figure 1; Mariani 2024; Ackerman 2025). Moreover, concern about obsolescence has grown in many other industries, making "obsolescence management" a new management practice with annual conferences, publications, and an international organization. Evidence of rising rivalry in general is seen in rapid product proliferation—many markets including

[1] We measure *revenue* productivity in this paper and refer to this measure generally as "productivity."

automobiles, breakfast cereals, and sports shoes have been flooded with new products.[2] A rough proxy for the overall number of new products in the economy is the number of new trademark registrations.[3] After decades of little growth, new trademark registrations have grown seven-fold since 1980 (see Figure 2), reflecting a major intensification of rivalry.

While this casual evidence hints at a major increase in technological rivalry, we obtain econometric estimates of this rivalry by extending the knowledge production function model to accommodate endogenous obsolescence. It is established that firm R&D reacts to technology competition (Mezzanotti and Simcoe 2023b). The notion we explore is that the more rivals in the same industry spend on R&D, the more likely they will develop technology that will partially or fully obsolesce the focal firm's knowledge stock. Obsolescence risk reduces expected returns, leading firms to reduce their R&D. We regress firm R&D against rivals' past R&D plus a range of control variables. We find rivals' R&D is strongly associated with lower R&D investment by the focal firm. Moreover, instrumental variable analysis suggests that this association is plausibly causal. We calculate the mean impact of rivals' R&D as a measure of technological rivalry, we find that this measure has increased substantially over time, beginning around the Dotcom boom, and this finding is robust to a variety of possible confounding factors such as industry competition conditions, markups, and firms' nonmanufacturing share. This measure of technological rivalry, which may differ from product market rivalry, also corresponds to common notions of industrial dynamism. For example, industries with higher technological rivalry tend to have higher exit and entry rates, more rapid turnover of market leaders, younger firms, and lower industry concentration. The industries with high technological rivalry include the dynamic software and biotech industries. Thus, both our econometric estimates and casual evidence support the hypothesis of rising technological rivalry.

Using our estimates of technological rivalry, we calculate endogenous obsolescence induced by rivals. We find that these lower bound estimates of obsolescence rates have

[2] From 1970 to 2012, the number of automobile models increased from 140 to 694, the number of breakfast cereals from 160 to 4945, the number of sports shoes from 5 to 3371, and so on with many other consumer products (Aichner and Coletti 2013).

[3] Trademarks protect words, names, symbols, or designs used to distinguish specific products. While not all products have registered trademarks, the number of new trademark registrations provides a first order measure of the number of distinct new products.

increased sharply since the 1990s.[4] These measures also allow us to compute R&D stocks and gross marginal returns to R&D, calculated as the output elasticity times the ratio of output to R&D stock. We find that gross returns to R&D have more than doubled since 1980, further supporting the hypothesis that R&D has become more effective. But *net* returns tell a different story. When obsolescence rises, firms must invest more R&D simply to replace knowledge lost to obsolescence, reducing the contribution to net new knowledge. Back-of-the-envelope calculations using actual R&D spending in manufacturing show that rising obsolescence may have substantially decreased the contribution of R&D to productivity growth since 1980. While productivity growth may well be affected by other factors such as rising markups or industry concentration, rising R&D does not necessarily contribute to higher productivity growth when obsolescence rises.

This result might seem counterintuitive. Doesn't rising technological rivalry, especially in the form of product proliferation, imply higher productivity? In Schumpeterian growth models, successful new products increase the level of productivity because they presumably offer better quality or price than the products they replace (Grossman and Helpman 1991; Aghion and Howitt 1992). But the *rate* of productivity growth depends on the relative productivities of new and old products, how much a new technology proportionally increases productivity relative to the replaced technology (the "inventive step"). Higher obsolescence implies that innovations are shorter lived and may therefore be less consequential. Indeed, if firms today introduce seven times as many new products each year as in 1980 yet the productivity growth rate remains roughly the same, the incremental improvement brought by each new product must be substantially less. While obsolescence is broader than just product replacement (see below), a variety of casual evidence hints at a decline in the quality of innovation so that higher obsolescence is not inconsistent with falling productivity growth.[5]

---

[4] This is a lower bound obsolescence rate because it only reflects the impact of rivals' R&D on the focal firm.

[5] Kalyani (2024) finds a decline in patent creativity. Also, R&D has substantially shifted away from "research" and toward relatively less consequential "development". Half of R&D was research in the 1960s; today only a quarter is (National Center for Science and Engineering Statistics, NSF 24-318). For example, the pharmaceutical industry has shifted to producing variations of top-selling drugs already on the market ("me-too" drugs), substantially reducing the novelty of innovation (Angell et al. 2010; Dranove et al. 2022; Cohen et al. 2025).

Fundamentally, our results differ from those of Bloom et al. (2020) because we use a different model relating R&D to productivity growth. In the knowledge production function model, the contribution of R&D to productivity growth arises from growth in firm knowledge stocks that are subject to obsolescence. In contrast, the Romer model used by Bloom et al. does not consider obsolescence. Instead, productivity growth is proportional to the *level* of R&D, not the growth of the R&D capital stock. Below, we test these two models in a panel of firm data. We find that firm productivity growth is uncorrelated with the level of firm R&D, but it is strongly associated with growth in the R&D stock. Klüppel and Knott (2023), using a different method, find a similar result on firm R&D. While Romer's equation might be applicable at the macro level over long periods of time, it is rejected in annual firm level data.

While many papers estimate elasticities and returns to R&D (see review in Hall et al. 2010), few have done so over long periods of time and with comprehensive data. Lucking et al. (2019), using Compustat data, find evidence of rising R&D elasticity. Li and Hall (2020), using BEA industry data, explore time-varying R&D depreciation rates for select industries.

Our paper is also closely related to recent research by Fort et al. (2025) who find that the elasticity of patent counts to R&D has risen since 1977 as well as citation weighted counts and counts of "breakthrough" patents. They suggest that patents no longer translate into economic growth as effectively as they once did—a conclusion consistent with our findings. Bloom et al. (2013) also look at how rival R&D affects focal firm R&D, but they do not draw inferences about obsolescence.

Of course, R&D is not the only factor contributing to slower productivity growth and models with variety of other factors have been proposed (Aghion et al. 2023; Akcigit and Ates 2021; Liu et al. 2022; Olmstead-Rumsey 2019; de Ridder 2024). This paper highlights the role of obsolescence and is consistent with rising R&D. In two related papers we explore how rivalry affects the growth of firms using new technology and the unequal distribution of R&D across firms, "Is R&D Rivalry Slowing the Growth of Productive Firms?" and "The Intangible Divide: Why do so few firms invest in innovation?" (Ando et al. 2025; Bessen and Wang 2024). Some portion of this text overlaps with those papers.

Our results suggest that R&D has not grown less effective. Instead, today R&D contributes less to productivity growth because of heightened technological rivalry, spurred in part precisely by the greater effectiveness of R&D. With greater rivalry, obsolescence is

higher and innovations tend to be shorter lived. The changing nature of innovation calls for policies that not only spur R&D, but also provide incentives to focus on long-lived innovations.

2. Knowledge Production Function Model

Production and R&D Capital

Our analysis is based on the workhorse knowledge production function model (Griliches 1979; for a review see Hall et al. 2010) that has been widely used in empirical investigation of the impact of R&D. Our exposition is based on this literature with one addition: we allow obsolescence to endogenously depend on rivals' R&D. The production of revenue is written

$$R = AX^{\alpha}K^{\beta}, \quad \alpha, \beta < 1 \tag{1}$$

where R is deflated firm revenue, X is a composite of input factors (labor, physical capital, and intermediate inputs), K is the firm "knowledge stock" (R&D stock defined below), and A captures other sources of productivity, knowledge spillovers from other firms, knowledge gained from learning-by-doing, and the quality of researchers.[6] We assume $\alpha < 1$ to capture diminishing returns to scale and/or markups; α equals one over markup in static equilibrium.[7] The marginal return to R&D is $\rho \equiv \frac{\partial R}{\partial K} = \beta \frac{R}{K}$.

This model is based on several assumptions that differ from the Romer model. First, the returns to each firm's R&D are diminishing ($\beta < 1$). This is usually attributed to a limited number of technological opportunities available to a firm at any time that are pursued in order of declining potential. Second, each firm has its own stock of knowledge that can be long-lived. In Romer, there is no firm-specific knowledge stock, no obsolescence, and all past knowledge spills over to all firms immediately. This knowledge stock is affected by obsolescence which we define as a loss in the commercial value of the

[6] Sometimes a term capturing knowledge spillovers is explicitly modeled using a sum of other firms' R&D weighted by technological proximity as in Bloom et al. (2013) where technological proximity is calculated using patent similarity. Instead, we capture the effect of knowledge spillovers in the revenue term; see discussion below.

[7] Markup $\mu = P/c$ where output price is *P* and unit cost is *c*. In static equilibrium, $\alpha = \frac{p_X X}{PY} = \frac{c}{P} = \frac{1}{\mu}$.

firm's knowledge stock. Firm knowledge is obsolesced when a firm's product is replaced by a rival's superior alternative. But obsolescence is broader than just product replacement. It occurs when standards change or when exogenous changes affect the value of the market (e.g., antimicrobial resistance). For example, in 2010, Apple discontinued support for Adobe Flash, a product used to build websites. Horton and Tambe (2025) document the extensive loss of knowledge value experienced both by Adobe and the many developers and firms that had used Flash to build websites.

The knowledge stock K represents the stock of commercially valuable knowledge; the obsolescence rate δ represents the reduction of knowledge that is no longer commercially valuable.[8] Following the literature, we can construct R&D capital stocks using the perpetual inventory method with an obsolescence rate, δ, and R&D investment I_t,

$$K_{t+1} = I_t + (1 - \delta)K_t. \tag{2}$$

Productivity and growth

We define revenue productivity, U, as the ratio of revenue to the composite input term

$$U \equiv \frac{R}{X^{\alpha}} = AK^{\beta}, \tag{3}$$

where equation (1) is substituted to obtain the latter term. Using lower case names to designate log variables and using the dot to designate time derivatives, we get an expression for productivity growth,

$$\begin{aligned} \dot{u} &= \dot{a} + \beta\dot{k} \\ &= \dot{a} + \beta\left(\frac{I}{K} - \delta\right), \end{aligned} \tag{4}$$

where the second expression is obtained by rearranging equation (2) and substituting.

The second term is the contribution of R&D to productivity growth and the term in parentheses is the rate of net R&D investment. This equation shows how rising obsolescence can reduce the rate of productivity growth at the firm level. Below, we make some quantitative estimates of the possible magnitude of this effect.

[8] This reduction is often called "depreciation" by analogy to physical capital, but that is a misnomer.

Note that Bloom et al. (2020) derive their measure of research productivity from a very different growth model. Drawing on Romer (1990), they propose that productivity growth should be proportional to the *level* of R&D, $\dot{u} = \phi_t \, I$ so that ϕ_t is a measure of research productivity.[9] Below we compare these growth equations in firm level data.

R&D Demand

Because the R&D stock is a long-lived asset, current R&D contributes to future returns, and the firms face a dynamic optimization problem to choose the level of R&D. We assume that conventional inputs X are statically optimized each period with respect to a common cost of inputs, p_X, generating operating profits $\Pi(K_t)$.[10] Then, given discount rate r and price of R&D p_K, the Bellman equation can be written

$$V(K_t) = \max_{K_{t+1}} \left[\Pi(K_t) - p_K(K_{t+1} - (1-\delta)K_t) + \frac{1}{1+r} V(K_{t+1}) \right]. \quad (5)$$

The first term captures the flow of profits based on the existing knowledge stock, the second term, using (2), represents the cost of R&D at price p_K, and the third term captures the continuation value of the firm with the increased knowledge stock.

Taking the first order maximizing condition, using the envelope theorem, rearranging and assuming the optimal policy is followed all years, we get

$$\frac{p_K}{1-\alpha}(r+\delta) = \rho. \quad (6)$$

This is similar to Jorgenson's user cost for depreciating physical capital (Jorgenson 1963); in equilibrium, firm invests until the marginal cost equals the marginal revenue. Assuming that on average firms follow a steady state growth path, $I = gK$ we derive an investment demand equation with fixed effects

$$\ln \hat{I} = \ln R - \ln(r+\delta) + \ln \beta - \ln p_K + FE + \epsilon. \quad (7)$$

[9] In Romer (1990) the ratio of productivity growth to real R&D is constant; in semi-endogenous growth models (such as Jones 1995) the ratio changes over time.

[10] $\Pi(K) = \max_X \left[AX^\alpha K^\beta - p_X X \right]$. The optimal level of inputs is $\hat{X} = \frac{\alpha \hat{R}}{p_X}$ so that $\Pi(K) = (1-\alpha)\hat{R}$.

Technological Rivalry and Endogenous Obsolescence

In the knowledge production function literature, researchers typically assume that the obsolescence rate (or the "R&D depreciation rate") is constant over time and uniform across firms in the same industry. We want to use a more general specification, allowing obsolescence to vary with rivals' R&D. The idea is that rivals' R&D raises expected future obsolescence. In this setting, each firm's obsolescence is a function of lagged rivals' R&D, $\delta_{it} = \delta(S_{it-1}),\ S_{it} = \sum_{\substack{j \neq i \\ j \in J}} I_{jt}$ where J specifies an industry (details below). We lag rivals' R&D to capture the typical gestation lag.

Then we interpret equation (7) as a reaction function, each firm taking rivals' R&D as given. To implement this more general specification, we substitute a flexible form for $\ln(r+\delta)$ in equation (7),

$$\ln(r+\delta) = \ln r + \gamma \ln S + \mu \ln R \ln S\,. \tag{8}$$

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 (7), sweeping the R&D price and discount rate into fixed effects to get an R&D demand equation

$$\ln I_{it} = \gamma_t + \gamma_J + \gamma_S \ln S_{it-1} + \gamma_x \ln S_{it-1} \cdot \ln R_{it} + \gamma_R \ln R_{it} + \epsilon_{it}, \tag{9}$$

where γ_t and γ_J denote the year and industry fixed effects. We estimate this equation below and subject it to a series of robustness checks. This equation is the firm's reaction function given the R&D of other firms. In the Appendix we show that in a symmetric Nash equilibrium, higher output elasticity β raises R&D spending of all firms, raising the obsolescence rate.

Of course, other firms' R&D affects the focal firm through another channel: knowledge spillovers. As other firms (not necessarily rivals) develop new knowledge, spillovers can benefit the focal firm via the variable A in the production function equation.

Bloom et al. (2013) use patent data to weight the R&D of other firms by their technical proximity to the focal firm, thus measuring potential spillover knowledge. However, since only 18 percent of R&D performing firms patent (Mezzanotti and Simcoe 2023a), we cannot construct such a measure for our more representative sample. Instead, we implicitly include the effect of knowledge spillovers in the $\ln R$ term in equation (9).

With estimates of the parameters in equation (9), we can estimate the impact of rivals' R&D on focal firm R&D as a measure of technological rivalry,

$$X_{it} = -(\hat{\gamma}_S \ln S_{it-1} + \hat{\gamma}_x \ln S_{it-1} \cdot \ln R_{it}). \quad (10)$$

In turn, we can invert equation (8) to obtain an estimate of endogenous obsolescence,

$$\hat{\delta}_{it} = r\left(e^{\hat{X}_{it}} - 1\right). \quad (11)$$

We discuss both estimates in our empirical analysis below.

3. Data

The data on R&D expenditures come from the Survey of Industrial Research and Development (SIRD) (1976–2007) and the Business R&D and Innovation Survey (BRDIS) (2008–18, renamed the Business Research and Development Survey in 2017). These are annual surveys of roughly 40,000 (less in the earlier years) for-profit, nonfarm businesses with five or more employees conducted by the US Census Bureau in collaboration with the National Science Foundation's National Center for Science and Engineering Statistics. In addition to the R&D data, firm-level sales and sample weights are drawn from the SIRD and BRDIS datasets. We use domestic R&D, but also check robustness using worldwide R&D.

A challenge for our analysis is that the scope of the sample in the R&D survey has changed, particularly since the early years of the SIRD datasets. Before 1992, the survey was mainly focused on large firms in manufacturing industries. Beginning in 1992, firms in several non-manufacturing industries and small firms were added. The BRDIS survey also substantially increased the scope of the sample frame. To conduct analysis with a consistent scope sample, we have constructed revised sample weights. We reweight the sample so that the composition of the sample every year from 1976 to 2018 is similar to that of the SIRD

datasets from 1976 to 1991.[11] The revised weights are used in the empirical analysis. We perform our analysis over four 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.

The SIRD and BRDIS datasets are linked to the Longitudinal Business Database (LBD) via SIRD -BRDIS Crosswalk developed by Cohen (2023). The LBD contains employment, age, and industry (NAICS code) of virtually all employer businesses in the United States. The data are further linked to establishment data in the manufacturing sector (NAICS sector 31-33) drawn from the quinquennial Census of Manufactures (CM) with data from the Annual Survey of Manufactures (ASM) for the intervening years, using census identifiers. The CM collects statistics from all establishments except for some very small ones, while the ASM is a survey of approximately 50,000 establishments.[12] 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.

Variables

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

[11] We first compute the sum of sample weights, provided by the SIRD and BRDIS datasets, of firms in each group defined by the employment size and industry in each year. Then, the average total weights in each group from 1976 to 1991 are computed and used as a basis. The sample weights in all years are reweighted such that the total weights in each group are the same as the average total weights computed for the years 1976-1991. The annual moments of R&D investment (mean, standard deviation, interquartile range) in the reweighted sample generate smooth series. We find our main result is robust to using the original sample weights (see fn. 14).

[12] The ASM data also includes sample weights to ensure its sample is representative of US establishments. However, these weights are correlated with those in the SIRD and BRDIS datasets, as larger firms are more likely to be included in both surveys, and the two sets of weights cannot be used simultaneously. Since selection into the R&D survey is more critical, we use the revised weights from the SIRD and BRDIS datasets in our analysis. We have also checked the robustness of our findings, though not released, using alternative weights constructed by adjusting the SIRD and BRDIS revised weights based on the relative weights of establishments within each firm in the ASM.

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

The data on revenue and three production inputs at the establishment level are drawn from the ASM, CM, and LBD. We also use these inputs to calculate markups using the Raval method (2023b; 2023a) for intermediates. 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.[13] The estimation is implemented by the prodest Stata package. We specify labor as a free variable, capital as a state variable, and intermediate inputs as a proxy variable. The firm takes last year's R&D as a state variable. Furthermore, we estimate the production function at each NAICS 3-digit industry, as the nature of production funcation may differ across industries. As reported in Table A.1, the average coefficients on labor, capital, and intermediate inputs across all 3-digit manufacturing industries are 0.24, 0.18, and 0.51, respectively. Once we estimate the production function, the TFP measure is obtained as in the equation above.

Instrumental variable for R&D. Regressions using R&D on the right hand side raise concern about a potential correlation between the error term and R&D expenditures, as firms may adjust R&D expenditures in response to productivity shocks. To mitigate this concern, we use lagged expenditures. But we also construct instruments for R&D expenditures by exploiting federal R&D tax credits, which generate supply-side shocks to firm-level R&D. Firms earn a tax credit on qualified research expenditures, known as the Research and Experimentation (R&E) Tax Credit. The credit is time-varying and firm-specific, as it depends on the statutory tax credit, subject to changes in the tax credit law, the corporate income tax rates, and firm-specific characteristics, such as R&D expenditures in

[13] 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). Note that the TFP estimates are for manufacturing production establishments and largely exclude capital and labor used in R&D.

the previous years. We compute the effective rate of R&D tax credit at the firm level, following Arque-Castells and Spulber (2022), and estimate the predicted value of R&D expenditures. The predicted value is based on an OLS regression, where the right-hand-side variables include log(1-R&D tax credit), firm fixed effects, and year fixed effects. The first-stage regression table is shown in the Appendix (Table A3). We then use the predicted R&D instead of actual R&D as an independent variable in regressions. A similar approach is adopted by Bloom et al. (2013) and Arque-Castells and Spulber (2022).

Firm characteristics. Heterogeneity in the returns to R&D is explored by constructing six different dummy variables: young firm (firm age less than 5), small firm (firm employees less than 100), exporter, market leader, firms with foreign R&D, and firms in a digital-intensive industry. The age and employment size are drawn from the LBD. Export data are taken from the CM and ASM datasets. The market leader is a firm with the largest sales in the NAICS 6-digit industry. Foreign R&D investments are reported by the SIRD and BRDIS datasets. Finally, digital-intensive industries are defined by the computer investments per worker at the industry level. The threshold for the binary variable is set at the median of NAICS 6-digit industries in the manufacturing sector. The computer investment data are available in the CM and ASM datasets only since 2002, so the digital-intensive industries are assumed to be time-invariant.

Returns to R&D. The returns to R&D are estimated as the product of output elasticity and the revenue-to-R&D stock ratio, as in equation (3). Here, revenue is measured at the firm level, as knowledge from R&D is shared across and increases the output of all establishments within each firm. We report the geometric mean of the returns, as the revenue-to-R&D stock ratios are highly dispersed. Note that Bloom et al. (2013) and Arque-Castells and Spulber (2022) report the median of their esimated R&D returns. The geometric mean and median yield similar results, but the release of geometric means is preferred to that of medians to protect confidentiality.

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. By industry we mean a group of firms whose products involve knowledge that might be helpful in developing replacement products for other firms in the industry. Rivals, in this sense, might not be product market competitors, but they are potential replacers. We construct a

lagged measure of rivals' R&D for firms in industry *J* as $S_{it-1} \equiv \sum_{j \neq i, j \in J} I_{j,t-1}$ where the industry is defined as the firm's primary 6-digit NAICS industry. Note that there is a possible bias estimating (9) using this rivalry measure because the dependent variable is implicitly related to S_{it-1}. In the Appendix, we analyze this bias and estimate it in our data, showing that it does not meaningfully affect our conclusions. We also instrument this variable in supplementary regressions. In Bessen and Wang (2024) we also use a weighted distance measure of rivals' R&D across different industries with similar results.

Obsolescence rates. Below we estimate expected endogenous obsolescence rates for each period by measuring the impact of rivals' R&D on focal firm R&D (see Table 4). These estimates are lower bound estimates because they don't include exogenous sources of obsolescence. To construct a continuous series of time-varying obsolescence rates, we assign the mean obsolescence rate to the center year of each period, interpolating between estimates and extrapolating at the beginning and end.

4. Empirical Findings

Revenue elasticity trends

We begin with a typical specification from the literature and then test variations for robustness. We initially use a regression of log TFP on an R&D stock,

$$\ln U_{it} = \beta \ln K_{it}^{15\%} + FE + \epsilon_{it}$$

where the R&D stock is calculated assuming a 15% R&D depreciation rate and the fixed effects are for detailed industry (NAICS 6-digit code) and year. To conduct consistent analysis across different sample periods, observations are weighted by our adjusted sample weights.[14] The results, shown in Table 1, Panel A, show a large increase in the estimated elasticities over time, rising from 0.009 in the first sample period (1977-1991) to 0.018 in the fourth (2008-2018). This increase is our base finding.

[14] We also conducted the analysis using the original sample weights rather than the adjusted weights and find a statistically significant increase in output elasticity at the 1% level from the first to fourth sample period. The same holds when using worldwide R&D instead of domestic R&D. Only the sign and significance level of these results are released from the Census Bureau (Approval Number: CBDRB-FY25-P2735-R12336) to minimize the volume of output and reduce disclosure risk.

However, these estimates have a problem: there is little evidence that R&D depreciates at 15% per annum; indeed, we argue below that obsolescence rates have increased over time. The problem is one of measurement error. To the extent that the true depreciation rate, d, differs from 15%, then $\ln K_{it}^{15\%} = \ln K_{it}^{d} - \mu_{it}$, where μ_{it} is measurement error. Generally, a single mismeasured right hand side variable will tend to attenuate the estimated coefficient (in this case, β). The degree of attenuation depends on the ratio of $var(\mu_{it})$ to $var(\ln K_{it}^{d})$.

Recognizing that their estimates were potentially biased, researchers responded by testing different depreciation rates (Griliches and Mairesse 1984; Bernstein 1998; Bernstein and Nadiri 1988; Hall and Mairesse 1995; Harhoff 1998). They found that the elasticity estimates are insensitive to the choice of depreciation over a range of depreciation rates, including the flow of R&D (100% depreciation). Hall, Mairesse, and Mohnen (2010) provide an explanation. Letting g_{it} be the growth rate of R&D of firm *i* at time *t*, and δ_{it} the R&D depreciation, they expand

$$\ln K_{it} = \ln I_{it} - \ln(\overline{g}_i + \overline{\delta}_i) + \nu_{it}$$

where $\overline{g}_i$ and $\overline{\delta}_i$ are the mean R&D growth rate and depreciation and ν_{it} is a complicated term capturing firm variations from the mean growth and depreciation rates. Using this in the elasticity regression, the second term is absorbed into the fixed effects. Hall et al. infer that the insensitivity of elasticity estimates implies that ν_{it} either has low variance relative to $\ln I_{it}$ or is uncorrelated with it. They conclude that reliable estimates of the output elasticity of R&D can be obtained using different depreciation rates to construct R&D capital or by using the flow of R&D investment. They report 13 studies that estimate output elasticities using R&D flow or R&D intensity (flow over sales).

Our estimates also appear insensitive to the choice of depreciation rate. Panel B of Table 1 uses the flow specification, $\ln U_{it} = \beta \ln I_{it-1} + FE + \epsilon_{it}$. The coefficient estimates are quite close to the estimates obtained using a 15% depreciation rate. This finding is helpful because it means we can estimate output elasticities over different time periods even if depreciation rates change between periods, as we propose below.

Panel C uses time-varying depreciation rates derived from estimates of lower-bound obsolescence rates that we obtain below (see Table 4). Again, the coefficient estimates are

close to those obtained using R&D flow. Given the robustness of elasticity estimates to choice of depreciation, we use flow estimates for the remainder of this table.

Another concern is that some third factor might be correlated with both productivity and R&D. Panel D uses the predicted R&D based on R&D tax treatment as an independent variable to address the endogeneity concern and shows a similar trend, where the elasticity increases from 0.010 in the first period to 0.019 in the fourth period.

Panel E controls for the number of establishments in each firm. In the baseline analysis, we examine the relationship between R&D expenditures at the firm level and TFP at the establishment level, assuming that new technologies developed in the firm can be shared across all establishments within the firm. But knowledge spillovers within firms may be imperfect (Adams and Jaffe 1996). To account for this, we add the log of the number of establishments within a firm as a control variable. The rise in elasticities is robust to this specification, while the additional control variable is not statistically significant except for the first sample period.

One concern is that our TFP estimates use fixed output elasticities of factor inputs over time. If, instead, they change over time, then our TFP measure might have a spurious trend. Panel F uses the TFP measure developed by the Collaborative Micro-productivity Project (Cunningham et al., 2023). In their estimation of TFP, factor elasticities are measured by the cost shares of corresponding inputs within each 6-digit NAICS industry, and these shares change each year. Again, we see an increase in the output elasticity of R&D over four sample periods that is robust to changing input elasticities. Relatedly, changing markups or returns to scale might be spuriously associated with the R&D elasticity.[15] In Appendix Table A2, we include the establishment markup in the regression. Exogenously rising market power might raise the returns to R&D; on the other hand, higher R&D likely raises markups. When we include markups in the regression, the output elasticity coefficients are unsurprisingly lower, but they nevertheless increase sharply over time, suggesting that the rise in output elasticity is not mainly driven by exogenously increasing markups.

[15] In our sample, markups measured using the Raval method with using intermediates rose from 1.40 to 1.65 (CBDRB-FY25-P2735-R12336). We use 4-digit industry estimates of cost shares; Foster et al. (2022) report smaller increases when more detailed industries are used. Markups might rise if returns to scale diminish ; we find that the sum of the input elasticities in our TFP regressions, have declined from the first sample period (1976–1991) to the fourth sample period (2008–2018) (CBDRB-FY25-P2735-R12452).

We also test our hypothesis with different fixed effects in Appendix Table A4 where we pool the data for the four time periods so that we can identify persistent firm or establishment fixed effects. While the magnitudes of the elasticity estimates unsurprisingly change with these different treatments, the basic finding of a large increase in output elasticity over time remains.

One concern with these estimates is that we exclude firms with zero R&D, as in much of the literature, possibly inviting sample selection bias. Several studies find that the rate of return on R&D is not fundamentally different for the firms with and without R&D (see Hall, Mairesse, and Mohnen 2010, page 1049). We conduct our own test and find no significant difference.[16] Also, as our samples change over time, perhaps some sample selection bias remains after we adjust the sample weights. As a further robustness check, we conduct a similar regression using a balanced panel of Compustat firms in the Appendix (Table A5). Despite major differences in samples, this analysis also finds significantly rising output elasticities.

Heterogeneity analysis

Table 2 explores the heterogeneity in output elasticities with respect to R&D, exploiting the comprehensive sample from the US Census. Young firms (less than five years old) and small firms (fewer than 100 employees) exhibit lower elasticity estimates than other firms, by 0.004 and 0.011, respectively. This indicates that their R&D expenditures have a weaker association with TFP compared to other firms. The smaller elasticity for small firms is not surprising—large firms are known to have higher R&D elasticities (Cohen and Klepper 1996). But this raises the possibility that large firms are driving the increase in the output elasticity over time. We test whether the gap between large firm and small firm elasticity has grown over time. We find that the gap has, in fact, shrunk, implying that the growth in the output elasticity with respect to R&D is observed in small firms as well as large firms, perhaps even more so.[17]

---

[16] Here, we construct a variable, $\mathrm{dhs}(R\&D_{it}) \equiv 2(R\&D_{it} - \mathrm{mean}(\mathrm{R\&D}))/(R\&D_{it} + \mathrm{mean}(\mathrm{R\&D}))$, which takes a value of -2 for firms with zero R&D. We run the same regression as in Table 1 (Panel A), replacing $\log(R\&D_{it-1})$ with $\mathrm{dhs}(R\&D_{it-1})$, and find that the elasticity has increased from the first to the fourth sample period. Approval Number: CBDRB-FY25-P2735-R12452.

[17] The difference in elasticities between large and small firms is statistically significant at the 1% level in the first sample period (1976–1991), but statistically insignificant in the fourth sample period (2008–2018). We also

In contrast, the elasticity estimates are larger among firms that operate in digital-intensive industries, measured by computer expenditures per worker, and among firms with the largest market share in their NAICS 6-digit industry. The interaction terms (0.007 and 0.010, respectively) are similar in magnitude to the base terms (0.006 and 0.008, respectively), suggesting that their elasticities are approximately twice as large as those of other firms. Finally, the last two columns examine the heterogeneity for firms with foreign R&D and exports. The interaction terms are statistically insignificant, suggesting that the presence of foreign operations or businesses with foreign markets may not be related to output elasticities. We also examined heterogeneity across NAICS 2-digit industries (NAICS 31, 32, and 33) but did not find statistically significant differences at the 5% level.

* * *

Why has the output elasticity of R&D risen? Generally, a rise in output elasticity is interpreted as a change in technology. Perhaps part of the rise may be attributed to a growing role of software in innovation. Note the rise is much greater in digital-intensive industries, and our data show that a growing share of R&D is spent on software development, rising from 20 percent in 2006 to 46 percent in 2021 (Moris 2019; CBDRB-FY24-P2735-R11743).

Technological rivalry

While higher R&D returns benefit the firm, the higher returns also benefit *rival* firms, perhaps raising rivals' investment and obsolescence risk. Previous work finds rivals' R&D is associated with substantially reduced firm R&D investment all else equal (Bessen and Wang 2024; Mezzanotti and Simcoe 2023b).[18] While knowledge spillovers from other firms' R&D (not necessarily rival firms) provide a benefit to firms, the evidence shows a substantial negative relation between rival firms' R&D and focal firm's R&D on average, suggesting a

estimate the same regression as in Table 2, including both the small-firm dummy and the young-firm dummy, and find that both terms are statistically significant at the 1% level, implying that both characteristics are relevant for explaining differences in elasticities. Approval Number: CBDRB-FY25-P2735-R12452.

[18] Bessen and Wang used a different sample (observations that are linked to the LBD revenue data and without some industries in NAICS 51 and 54), with different firm size measures, and additional right hand side variables (firm age, number of industries, number of zip codes, and number of rivals' patents of each firm).

response to technological rivalry. Here we want to explore how this technological rivalry has changed over time. We begin estimating our basic R&D investment demand equation, (9), over four periods since 1976.

Table 3 shows these 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. We use the inverse hyperbolic sine (asinh) rather than the log of rivals' R&D because this variable can be very small for some industries. Panel A shows the simple regression with just the rivals' R&D term on the right-hand side; the coefficients are negative and roughly larger over time. Panel B adds terms involving log real revenues to proxy for the size of the customer base. For 2008 and after, we use worldwide net sales from BRDIS. For earlier years, however, SIRD does not consistently report worldwide sales, so we use domestic net sales interacted with a dummy variable indicating whether the firm has foreign R&D spending, an indicator of foreign activities.[19]

The coefficients of rivals' investment, shown in the first row of Panel B, are negative, meaning that rival firms' R&D in the last period is negatively associated with focal firms' R&D; and the magnitude increases substantially over time. We also test for industry variation but find no statistically significant differences.[20] The bottom row shows the combined impact of the two rival investment terms calculated at the sample means. These have increased 0.57 log points.

There are several possible concerns with this regression. One is endogeneity. The focal firm and rivals might both experience common shocks that affect their R&D productivity, making rivals' R&D correlated with the error term. This is not too worrisome for our analysis because this would imply that the coefficient on rivals' R&D would be biased upwards. Since our estimates of these coefficients are negative, this would mean that the true coefficients are even more negative. 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, we show that this incentive does not alter the

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

[20] In the sample of broader industries, we test for heterogeneity across four industry groups (i.e., manufacturing, information and professional services, retail and wholesale, and others). The differences are not statistically significant at the 5% level.

basic form of equation (9). To address this concern empirically, Panel A shows the regression without the sales-related terms. The coefficients for rivals' R&D still increase substantially over time although the last period shows a dip. To address both sources of endogeneity, we instrument sales and rivals' R&D in Appendix Tables A6 and A7. To obtain predicted sales, we regress firm log sales on firm age and a firm fixed effect. We also instrumented rivals' R&D by regressing log R&D of every firm against log R&D tax cost and a firm fixed effect, obtaining the prediction, and calculating the weighted sum as in the base measure of rivals' R&D. The Appendix reports the details of this instrument, robustness checks, and Table A7 shows the base regression with the predicted values for both sales and rivals' R&D. Again, the coefficients on rivals' R&D are similar.[21] All of these variations show a rise in technological rivalry.

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. In Table A8 in the Appendix we include a variety of other controls 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.[22] The significant coefficients on these control variables suggest that market competition affects R&D investment. But these controls do not diminish the coefficients on rivals' R&D, suggesting that rivals' R&D independently affects focal firm R&D and is more than just a proxy for rivals' market share, etc. We also tested specifications (for which only the signs of the results are released) with controls for a variety of IO competition concerns.[23] All of these

[21] We conducted a number of other robustness checks that are not reported, including alternative sales measures, a sample selection correction using inverse propensity weights, excluding observations with imputed R&D, and an alternative R&D instrument that excluded rivals in the same state as the focal firm. Results were all similar.

[22] 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).

[23] 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

specifications still showed a statistically significant increase in the (negative) coefficient on rivals' R&D.

The instrumental variable analysis further suggests that the association between rivals' R&D and focal firm investment is plausibly causal. If so, what mechanism produces this effect? Our model suggests that rival R&D creates innovations that partially or fully make focal firm knowledge obsolete. There are other possible channels, however. Perhaps rival R&D spills over and allows the focal firm to reduce R&D by copying rival innovations. If so, we would expect rivals' patents to reduce copying, but earlier work found that while rivals' R&D strongly affects focal firm R&D, rivals' patents do not (Bessen and Wang 2024). Also, studies find that external R&D does not diminish focal firm R&D (Bloom et al. 2013) or might even increase it (Cohen and Levinthal 1989; 1990). Another mechanism might arise if rivals' R&D increases the competition for R&D inputs, mainly scientists and engineers. However, we do not see a rise in the wage premiums of these occupations.[24] Perhaps these labor markets are increasingly monopsonistic or face rising adjustment costs, constraining wage effects. But the rivalry we are concerned about occurs nationally while labor market competition is substantially local. Moreover, in the Appendix we provide evidence that adjustment costs and monopsony are unlikely to have raised effective R&D costs.

We conclude that the coefficients on rivals' R&D are plausible measures of technological rivalry, they have been increasing over time, and they correspond to rising obsolescence. These measures of technological rivalry also correspond generally to common notions of industrial dynamism. In Table A9 in the Appendix, we regress industry mean characteristics against industry means of the measure of rivalry (and also log R&D). We find that industry technological rivalry is positively associated with the industry's firm entry rate, exit rate, and disruption of market leaders, and it is negatively associated with industry concentration and firm age. Moreover, the industries with the highest levels of technological rivalry (Appendix Table A10) include well-known dynamic industries.

---

neck & neck competition vs. "unlevelled" competition (below/above median industry markup; also, below/above industry TFP dispersion).

[24] Using the Current Population Survey from 1988 to 2018, the ratio of the wages of scientists and engineers to the wages of all occupations fell about 5%.

Estimating obsolescence rates

Greater technological rivalry implies a higher risk of obsolescence. Equation (11) provides a method to estimate a lower-bound obsolescence rate based on the regression used in Table 3. The estimate is a lower bound because it only includes obsolescence arising from rivals' R&D; it does not include exogenous sources of obsolescence such as the growth of microbial resistance to antibiotics. The first line of Table 4 shows estimates of these obsolescence rates with bootstrapped standard errors; obsolescence rates increased from 12% in the first sample period to 32% in the last sample period. These estimates can be compared loosely to R&D depreciation rates reported in the literature and to those used by statistical agencies. The BEA uses R&D depreciation rates ranging from 10 percent to 40 percent and software depreciation rates ranging from 33 percent to 55 percent. Li and Hall (2020) estimate rates for different industries for the period 1987-2007 from 6 percent to 73 percent. They also review estimates from the previous literature. Excluding outlier studies, the estimated R&D depreciation rates range from 11 to 41 percent.[25] Huang and Diewert (2011) estimate rates for US manufacturing industries from 1953-2000 ranging from 1 percent to 29 percent overall. Thus, our obsolescence rates are loosely similar to those in the recent literature. However, the importance of our estimates lies not in their levels, but in the finding that they have increased dramatically over the last 40 years.

Of course, rising rivalry is not the only factor affecting obsolescence rates. Other factors that might contribute to shorter lived innovation include a decline in the share of R&D going to research as opposed to development (Arora et al. 2020) and less patient investors (Narain 2024).

Marginal returns to R&D

The marginal return to R&D provides a measure of R&D effectiveness different from the output elasticity of R&D. With estimates of obsolescence, we can construct R&D capital stocks and calculate the gross marginal returns to R&D. Table 4 reports the estimated returns to R&D, $\rho = \beta \frac{R}{K}$. We present estimates using our estimated time-varying

[25] Including outliers, the estimates range from -11 percent to 100 percent. A paper using a retrospective inventor survey finds relatively low estimates of obsolescence (de Rassenfosse and Jaffe 2018).

obsolescence rate and the standard 15 percent depreciation to construct the R&D stocks. We calculate the returns using the geometric mean. Both estimates show marginal returns that more than doubled from the first period to the last. Other fixed depreciation rates yield similar results. Thus, rising marginal returns also imply a substantial increase in R&D effectiveness.

Rising returns provide additional support for the hypothesis of rising obsolescence. In equilibrium, firms should adjust their investment so that the marginal return equals the marginal "user cost" of R&D as in equation (6). Consider the components of user cost: the after-tax price of R&D, α (which equals one over the markup), real interest rates, and obsolescence rates. First, consider the price of performing R&D. The R&D figures we use have been deflated by the BEA R&D price deflator so changes in the price of R&D have already been incorporated into our estimates of returns.[26] In any case, the R&D deflator closely tracks the GDP deflator. But the after-tax cost of R&D has declined substantially as the Federal government and states have offered increasingly generous tax treatment of R&D.[27] The cost of R&D cannot account for a doubling in the returns to R&D; the changes are modest and in the wrong direction. Also, depending on how they are measured, markups have increased, corresponding to a decline in α and a lower user cost.[28]

Nor can interest rates account for the doubling; interest rates have fallen substantially. For instance, real 10-year Treasury yields have fallen from 6.9% in 1982 to 1.2% in 2018.[29] The user cost of R&D should also reflect risk premiums, but there is little reason to expect that the risk of R&D has grown substantially. For instance, the volatility of stock market returns shows little change since the early 1980s.[30] Of course, it is possible that a "wedge" might cause the returns to exceed the measured marginal cost. In the Appendix, we consider whether changing R&D adjustment costs or changing monopsony in R&D

---

[26] U.S. Bureau of Economic Analysis, "Table 5.6.4. Price Indexes for Private Fixed Investment in Intellectual Property Products by Type".

[27] The mean R&D tax parameter over all states declined 32 percent from 1976 to 2018.

[28] See 15. Note that $\frac{1}{1-\alpha} = \frac{\mu}{\mu-1}$.

[29] Federal Reserve Bank of Cleveland, 10-Year Real Interest Rate [REAINTRATREARAT10Y], retrieved from FRED, Federal Reserve Bank of St. Louis

[30] Bloomberg, "Stock Price Volatility," retrieved from The World Bank Group Global Financial Development Database.

input markets might account for the large rise in return to R&D. The evidence weighs against such an interpretation.

Thus, having ruled out plausible explanations for rising R&D returns based on rising R&D prices, interest rates, adjustment costs, and monopsony, the process of elimination leaves us with one candidate explanation: rising obsolescence rates.

Productivity growth and R&D

How do rising output elasticity of R&D and rising obsolescence affect productivity growth? To understand the significance of our empirical findings, we need to specify the relationship between productivity growth and R&D. The knowledge production model describes this relationship in equation (4), $\dot{u} = \dot{a} + \beta\dot{k}$, where productivity growth increases with growth in the R&D stock. On the other hand, Bloom et al. (2020), drawing on the growth literature, propose that productivity growth should be proportional to the *level* of R&D, $\dot{u} = \phi_t I$.

Table 5 tests the empirical relevance of these two equations for firm level productivity growth using our data pooled across periods.[31] Columns 1 and 2 show the version derived from Romer, measuring the R&D level in billions of deflated R&D expenditures. Column 2 adds firm and year fixed effects. The level of R&D is not substantially correlated with firm productivity growth (see also Klüppel and Knott 2023).[32] Columns 3 and 4 show the version derived from the knowledge production function (labelled "Griliches") using time-varying obsolescence rates to construct the stock variable. Here, the growth in the R&D stock is highly significant. This is hardly surprising because the equation estimated is pretty much just a first-differenced version of equations estimated in Table 1 and in the literature.[33] The Romer model reflects concerns about the aggregate economy over long periods of time, but does not, apparently, fit firm behavior.

[31] Ekerdt (2024) proposes a model where the growth of R&D labor and non-labor costs contribute separately. However, the necessary data are not available before 2008.

[32] The coefficient in column 2 is statistically significant but negative and extremely small.

[33] The coefficients are somewhat smaller than those in Table 1 but errors in measuring R&D tends to attenuate coefficients (Griliches and Hausman 1986). Also, we obtain very similar coefficients using 15 percent depreciation.

Of course, aggregate output is the sum of firm outputs, and a simple back-of-the-envelope calculation establishes the quantitative importance of rising obsolescence. We aggregate firm effects by assuming that the manufacturing sector consists of symmetric firms. Using data on real R&D for the manufacturing sector,[34] we calculate the R&D stock using time varying obsolescence estimates. If we further assume that the returns from spillovers are 4 times the direct returns from R&D and that the growth of spillovers vary with the growth of the net stock ($\dot{a} = 4\beta\dot{k}$), then we get

	1976-1991	1992-1999	2000-2007	2008-2018
Growth of R&D stock	4.9%	2.7%	-3.7%	1.0%
β	0.010	0.010	0.013	0.018
Contribution to productivity growth (including spillovers)	0.24%	0.13%	-0.24%	0.02%

The contribution of R&D to productivity growth fell substantially despite rising output elasticity of R&D and even became negative during the Dot-Com bust.[35] Although these calculations are crude and not realistic, they demonstrate the possible quantitative importance of obsolescence.

5. Conclusion

Our evidence challenges the hypothesis that research productivity has substantially declined. Instead, we find that a marginal increase in R&D yields a considerably greater proportional increase in firm productivity than it did in the past. We also find that gross marginal returns to R&D have increased substantially. Our econometric analysis finds that this rising effectiveness of R&D has apparently helped rivals also become more effective, raising technological rivalry and the risk of obsolescence. Our results imply that while innovative "ideas" are *not* apparently harder to find, it may be harder to translate them into sustained productivity growth. Fort et al. (2025), looking at firm growth rates, make a similar point.

[34] Thanks to Corby Garner from the BLS.

[35] Excessive scrapping of research, as likely happened with DotCom boom investments, can have a temporary negative effect on productivity growth.

Our results differ from those of Bloom et al. (2020) because our analysis is based on a different model of the relationship between R&D and productivity growth. Our estimates derive from the knowledge production function model where firm productivity growth increases with the growth of the firm knowledge stock. A large literature confirms the empirical relevance of this approach. Bloom et al., instead, base their analysis on the assumption, derived from Romer (1990) and the growth literature, that firm productivity is an increasing function of firm level of R&D or, equivalently, the number of researchers. But our tests and those of Klüppel and Knott (2023) reject this relationship in firm data. Romer's equation may make sense at the macro level in the long term, but it lacks empirical support at the firm level.[36]

Because obsolescence slows the growth of the knowledge stock, rising R&D does not necessarily increase the rate of productivity growth, as we find. Moreover, rising obsolescence implies that innovations are shorter lived on average. This raises the possibility that higher obsolescence shortens the time horizons firms consider when deciding which R&D projects to pursue, how many workers to hire, and whether to the adopt others' technologies. Our analysis in a related paper suggests that higher obsolescence and this sort of "short termism" have a substantial effect on the growth of productive firms that is important to job reallocation (Ando et al. 2025). Further research is needed to understand the full extent to which obsolescence slows the translation of innovation into aggregate productivity growth. Another related paper finds that heterogeneous obsolescence rates may contribute to an increase in the concentration of firms performing R&D (Bessen and Wang 2024), possibly promoting industry concentration. These analyses suggest that R&D policy needs to do more than provide incentives to encourage greater R&D; it needs to promote the translation of innovations into productivity growth. Policies are needed to foster innovation with lower obsolescence, perhaps by encouraging more research on longer-lived innovations relative to short-lived development projects.

[36] It is beyond the scope of this paper to explore a growth model based on the knowledge production function. However, it is worth noting that such a model does not have the same scaling problem as the Romer model where more populous countries (those with more researchers) have higher productivity growth (Jones 1995).

Tables

Table 1. Estimates of the Elasticity of TFP with respect to R&D

	(1)	(2)	(3)	(4)
Period	1977-1991	1992-1999	2000-2007	2008-2018
A. Dependent variable: Log TFP (Levinsohn-Petrin), OLS				
Log R&D stock (15%)	0.009***	0.009***	0.014***	0.018***
	(0.001)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.484	0.467	0.429	0.487
Observations	260,000	138,000	123,000	162,000
B. Dependent variable: Log TFP (Levinsohn-Petrin), OLS				
Log $R\&D_{t-1}$	0.010***	0.010***	0.013***	0.019***
	(0.001)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.485	0.470	0.394	0.435
C. Dependent variable: Log TFP (Levinsohn-Petrin), OLS				
Log R&D stock (varying δ)	0.010***	0.008***	0.011***	0.019***
	(0.000)	(0.000)	(0.001)	(0.001)
Adjusted R^2	0.486	0.464	0.415	0.487s
D. Dependent variable: Log TFP (Levinsohn-Petrin), IV				
Log $R\&D_{t-1}$ predicted	0.010***	0.009***	0.014***	0.019***
	(0.001)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.480	0.469	0.391	0.434
E. Dependent variable: Log TFP (Levinsohn-Petrin), OLS				
Log $R\&D_{t-1}$	0.013***	0.012***	0.014***	0.018***
	(0.002)	(0.003)	(0.003)	(0.002)
Log No. of establishments	-0.009***	-0.007	-0.000	0.001
	(0.003)	(0.005)	(0.005)	(0.004)
Adjusted R^2	0.485	0.470	0.394	0.435
F. Dependent variable: Calculated Log TFP, OLS				
Log $R\&D_{t-1}$	0.007***	0.009***	0.009***	0.012***
	(0.001)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.610	0.630	0.450	0.509

Note: Standard errors are shown in parentheses and are clustered by firm (*** p<0.01, ** p<0.05, * p<0.10). All regressions have year and 6-digit NAICS fixed effects and use adjusted sample weights. The Levinsohn-Petrin TFP estimates used separate regressions for each 3-digit NAICS industry. Panel F uses TFP calculations based on cost shares. The details of the instrumental variable regression are described in text. The R&D stock in Panels A and C is calculated using a fixed 15% and an estimated time-varying obsolescence rate, respectively. The number of observations is rounded to protect confidentiality. Observation counts for other panels in the corresponding sample periods are similar and therefore omitted from the table. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155, CBDRB-FY26-P2735-R12846).

Table 2. Heterogeneity of Elasticities

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Log TFP (Levinsohn-Petrin), OLS						
Log $R\&D_{t-1}$	0.011***	0.009***	0.006***	0.008***	0.009***	0.010***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Log $R\&D_{t-1}$						
x young firm	-0.004***					
	(0.001)					
x small firm		-0.011***				
		(0.003)				
x digital firm			0.007***			
			(0.002)			
x market leader				0.010***		
				(0.001)		
x foreign R&D					0.000	
					(0.001)	
x exporter						0.000
						(0.001)
Adjusted R^2	0.481	0.481	0.481	0.483	0.481	0.482

Note: Standard errors are shown in parentheses and are clustered by firm (*** p<0.01, ** p<0.05, * p<0.10). All regressions have year and 6-digit NAICS fixed effects and use adjusted sample weights. The regressions cover 683,000 observations from 1977-2018 (the last column only 663,000). The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

Table 3. R&D Investment and Technological Rivalry

Period	1977-1991 (1)	1992-1999 (2)	2000-2007 (3)	2008-2018 (4)
Dependent variable: Log R&D				
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	20500	13000	17500	35000
B. Regression with revenue terms				
Asinh(rival R&D$_{t-1}$)	-0.867*	-0.750*	-1.667***	-2.134***
	(0.461)	(0.408)	(0.629)	(0.373)
Log(revenue) x asinh(rival R&D$_{t-1}$)	0.059	0.0205	0.068	0.104***
	(0.041)	(0.030)	(0.045)	(0.028)
Foreign = 0 x log(revenue)	0.569***	0.794***	0.620***	
	(0.127)	(0.076)	(0.089)	
Foreign = 1 x log(revenue)	0.684***	0.840***	0.671***	
	(0.131)	(0.074)	(0.089)	
Log(revenue)				0.397***
				(0.054)
Adjusted R^2	0.677	0.763	0.716	0.575
Observations	20500	13000	17500	27000
Mean impact ($\overline{X_{it}}$)	1.146	0.882	1.586	1.717

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. The number of observations is rounded to protect confidentiality. 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. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743, CBDRB-FY25-P2735-R12155).

Table 4. Obsolescence and Gross Returns to R&D

	1976-1991	1992-1999	2000-2007	2008-2018
Estimated obsolescence rate	.123	.080	.239	.315
	(0.058)	(0.028)	(0.060)	(0.075)
Gross marginal returns				
with varying obsolescence rate	.117	.097	.181	.287
with 15% depreciation	.088	.058	.216	.235

Note: The obsolescence rates are calculated as described in the text from the regressions in Table 3. The standard errors of obsolescence rates are bootstrapped and shown in parentheses. To estimate the returns to R&D, output elasticities are first calculated by running the regressions shown in Table 1, (Panels C and A), using R&D capital stocks constructed with the specified obsolescence rate. These elasticities are then multiplied by the ratio of firm output to R&D stock. The table reports geometric means for each period. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155, CBDRB-FY26-P2735-R12846).

Table 5. Productivity Growth and Obsolescence

Dependent variable: First differenced Log TFP				
	Romer Model		Griliches Model	
	(1)	(2)	(3)	(4)
R&D (billions $2012)	4.38E-10	-6.28e-09***		
	(0.0000)	(0.0000)		
Δ Log R&D stock			0.0081***	0.0061***
			(0.0008)	(0.0009)
Fixed Effects	--	Firm, year	--	Firm, year
Adjusted R-squared	.000	.000	.012	.012
N	674,000	674,000	674,000	674,000

Note: Standard errors are shown in parentheses and are clustered by firm (*** p<0.01, ** p<0.05, * p<0.10). Regressions include fixed effects as shown and use adjusted sample weights. The R&D stock is calculated using varying obsolescence rates. The number of observations is rounded to protect confidentiality. (CBDRB-FY26-P2735-R12846).

Figures

Figure 1. Innovation investment relative to value-added
Source: BEA; TFP growth estimates from BLS [rndgro3]

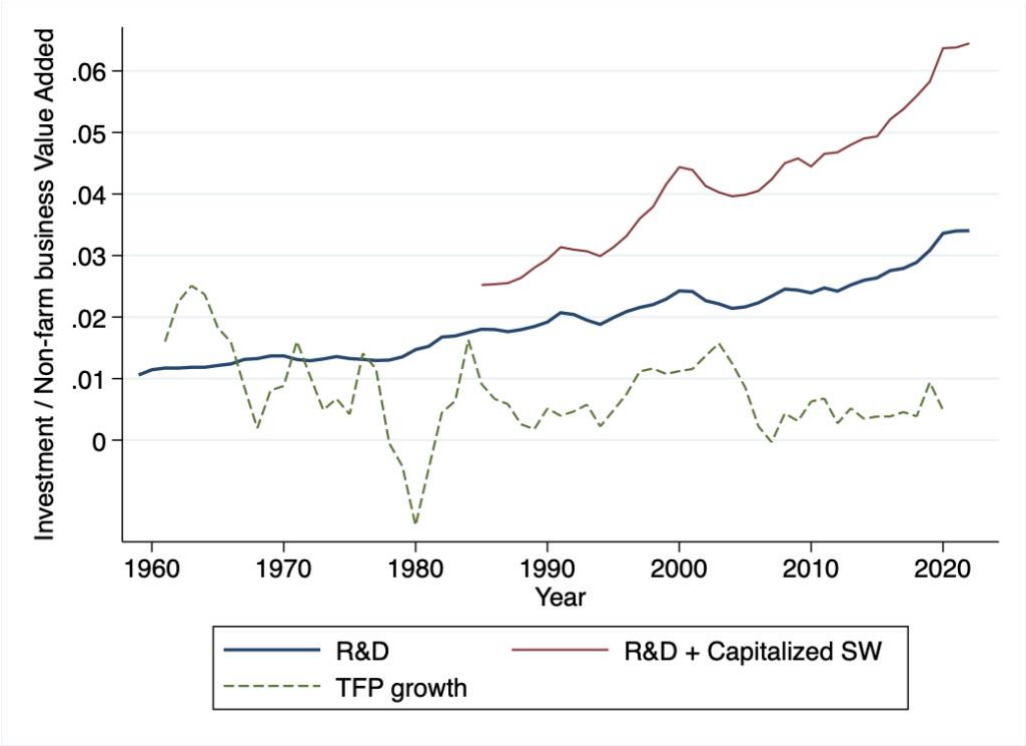
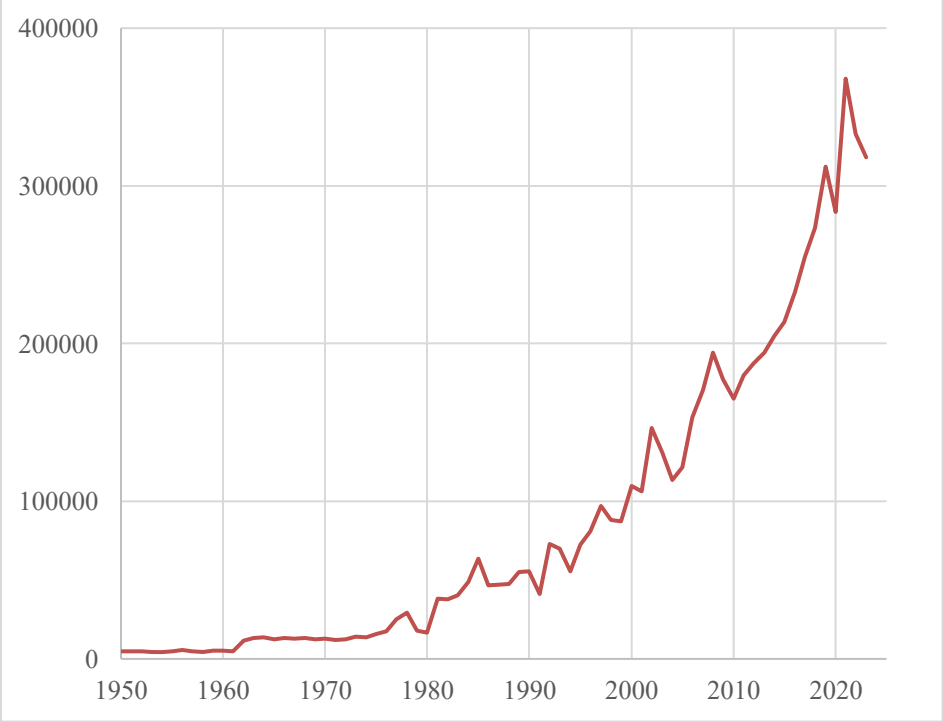


Figure 2. Number of New US Trademark Registrations



Data source: USPTO

References

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

Ackerman, Kathryn. 2025. "Component Obsolescence Is Rising: Why Is It Increasing and How to Proactively Mitigate the Risks." Sourceability, February 26. https://sourceability.com/post/how-to-mitigate-electronic-component-obsolescence-risks.

Adams, James D, and Adam B Jaffe. 1996. "Bounding the Effects of R&D: An Investigation Using Matched Establishment-Firm Data." National bureau of economic research Cambridge, Mass., USA.

Aghion, Philippe, Antonin Bergeaud, Timo Boppart, Peter J Klenow, and Huiyu Li. 2023. "A Theory of Falling Growth and Rising Rents." *Review of Economic Studies* 90 (6): 2675–702.

Aghion, Philippe, and Peter Howitt. 1992. "A Model of Growth Through Creative Destruction." *Econometrica: Journal of the Econometric Society*, 323–51.

Aichner, Thomas, and Paolo Coletti. 2013. "Customers' Online Shopping Preferences in Mass Customization." *Journal of Direct, Data and Digital Marketing Practice* 15 (1): 20–35.

Aizcorbe, Ana. 2005. "Moore's Law, Competition, and Intel's Productivity in the Mid-1990s." *American Economic Review* 95 (2): 305–8. https://doi.org/10.1257/000282805774669655.

Akcigit, Ufuk, and Sina T Ates. 2021. "Ten Facts on Declining Business Dynamism and Lessons from Endogenous Growth Theory." *American Economic Journal: Macroeconomics* 13 (1): 257–98.

Alston, Julian M, and Philip G Pardey. 2022. *Are Ideas Really Getting Harder to Find?*

Ando, Yoshiki, James Bessen, and Xiupeng Wang. 2025. *Is R&D Rivalry Slowing the Growth of Productive Firms?* Working paper.

Angell, Marcia, Senior Lecturer in Social Medicine at Harvard Medical School, is former Editor of the New England Journal of Medicine, and author of The Truth About the Drug Companies. 2010. "Big Pharma, Bad Medicine." *Boston Review*, May 1. https://www.bostonreview.net/forum/angell-big-pharma-bad-medicine/.

Arora, Ashish, Sharon Belenzon, Andrea Patacconi, and Jungkyu Suh. 2020. "The Changing Structure of American Innovation: Some Cautionary Remarks for Economic Growth." *Innovation Policy and the Economy* 20 (1): 39–93.

Arque-Castells, Pere, and Daniel F Spulber. 2022. "Measuring the Private and Social Returns to R&D: Unintended Spillovers versus Technology Markets." *Journal of Political Economy* 130 (7): 1860–918.

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*.

Bernstein, Jeffrey I. 1998. "Factor Intensities, Rates of Return, and International R&D Spillovers: The Case of Canadian and US Industries." *Annales d'Economie et de Statistique*, 541–64.

Bernstein, Jeffrey I, and M Ishaq Nadiri. 1988. "Interindustry R&D Spillovers, Rates of Return, and Production in High-Tech Industries." National Bureau of Economic Research Cambridge, Mass., USA.

Bessen, James, and Xiupeng Wang. 2024. *The Intangible Divide: Why Do so Few Firms Invest in Innovation?*

Bloom, Nicholas, Charles I Jones, John Van Reenen, and Michael Webb. 2020. "Are Ideas Getting Harder to Find?" *American Economic Review* 110 (4): 1104–44.

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

Card, David. 2022. "Who Set Your Wage?" *American Economic Review* 112 (4): 1075–90.

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.

Cohen, Wesley M, Matthew J Higgins, William D Miles, and Yoko Shibuya. 2025. *Blockbusters, Sequels and the Nature of Innovation*. National Bureau of Economic Research.

Cohen, Wesley M, and Steven Klepper. 1996. "A Reprise of Size and R & D." *The Economic Journal* 106 (437): 925–51.

Cohen, Wesley M, and Daniel A Levinthal. 1989. "Innovation and Learning: The Two Faces of R & D." *The Economic Journal* 99 (397): 569–96.

Cohen, Wesley M, and Daniel A Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35 (1): 128–52.

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.

Dranove, David, Craig Garthwaite, and Manuel Hermosilla. 2022. "Does Consumer Demand Pull Scientifically Novel Drug Innovation?" *The RAND Journal of Economics* 53 (3): 590–638.

Ekerdt, Lorenz. 2024. "The Role of R&D Factors in Economic Growth." *Center for Economic Studies Working Papers*, no. CES 24-69.

Fort, Teresa C, Nathan Goldschlag, Jack Liang, Peter K. Schott, and Nikolas Zolas. 2025. "Growth Is Getting Harder to Find, Not Ideas." *Center for Economic Studies Working Papers*, no. CES 25-21 (April).

Foster, Lucia S, John C Haltiwanger, and Cody Tuttle. 2022. *Rising Markups or Changing Technology?* National Bureau of Economic Research.

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)*.

Gordon, Robert J. 2017. *The Rise and Fall of American Growth: The US Standard of Living since the Civil War*. Princeton University Press.

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

Griliches, Zvi. 2009. "Productivity, R&D, and the Data Constraint." In *The Economic Impact of Knowledge*. Routledge.

Griliches, Zvi, and Jerry A Hausman. 1986. "Errors in Variables in Panel Data." *Journal of Econometrics* 31 (1): 93–118.

Griliches, Zvi, and Jacques Mairesse. 1984. *Productivity and R&D at the Firm Level*. National Bureau of Economic Research, Inc.

Grossman, Gene M, and Elhanan Helpman. 1991. "Quality Ladders in the Theory of Growth." *The Review of Economic Studies* 58 (1): 43–61.

Hall, Bronwyn H, and Jacques Mairesse. 1995. "Exploring the Relationship between R&D and Productivity in French Manufacturing Firms." *Journal of Econometrics* 65 (1): 263–93.

Hall, Bronwyn H, Jacques Mairesse, and Pierre Mohnen. 2010. "Measuring the Returns to R&D." In *Handbook of the Economics of Innovation*, vol. 2. Elsevier.

Harhoff, Dietmar. 1998. "R&D and Productivity in German Manufacturing Firms." *Economics of Innovation and New Technology* 6 (1): 29–50.

Hochbaum, Dorit, Erick Moreno-Centeno, Phillip Yelland, and Rodolfo Catena. 2011. "Rating Customers According to Their Promptness to Adopt New Products." *Operations Research* 59 (October): 1171–83. https://doi.org/10.2307/41316021.

Horton, John J, and Prasanna Tambe. 2025. "The Death of a Technical Skill." *Information Systems Research*.

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.

Jones, Charles I. 1995. "R & D-Based Models of Economic Growth." *Journal of Political Economy* 103 (4): 759–84.

Jorgenson, Dale W. 1963. "Capital Theory and Investment Behavior." *The American Economic Review* 53 (2): 247–59.

Kalyani, Aakash. 2024. "The Creativity Decline: Evidence from US Patents." *Federal Reserve Bank of St. Louis, Research Division*.

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.

Klüppel, Leonardo, and Anne Marie Knott. 2023. "Are Ideas Being Fished Out?" *Research Policy* 52 (2): 104665.

Kortum, Samuel. 1993. "Equilibrium R&d and the Patent–R&d Ratio: Us Evidence." *The American Economic Review* 83 (2): 450–57.

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.

Liu, Ernest, Atif Mian, and Amir Sufi. 2022. "Low Interest Rates, Market Power, and Productivity Growth." *Econometrica* 90 (1): 193–221.

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

Mariani, Michael. 2024. "Why Mitigating Obsolescence During Electronic Component Selection Is a Critical Risk Management Strategy - Z2Data." Insights, October 28. https://www.z2data.com/insights/mitigating-obsolescence-during-electronic-component-selection-is-critical.

Mezzanotti, Filippo, and Timothy Simcoe. 2023a. "Innovation and Appropriability: Revisiting the Role of Intellectual Property." *NBER Working Paper*, no. 31428.

Mezzanotti, Filippo, and Timothy Simcoe. 2023b. *Research and/or Development? Financial Frictions and Innovation Investment*. National Bureau of Economic Research.

Moris, Francisco. 2019. *Software R&D: Revised Treatment in U.S. National Accounts and Related Trends in Business R&D Expenditures*. NSF. https://www.nsf.gov/statistics/2019/nsf19315/nsf19315.pdf.

Narain, Namrata. 2024. "How Patient Is Venture Capital?" https://drive.google.com/file/d/1rz5-BR8rh2Hdm8AQ2hCTphi5PeJ3qFMo/view.

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

Olmstead-Rumsey, Jane. 2019. "Market Concentration and the Productivity Slowdown." *MPRA Paper* 93260.

Peters, Ryan H, and Lucian A Taylor. 2017. "Intangible Capital and the Investment-q Relation." *Journal of Financial Economics* 123 (2): 251–72.

Rassenfosse, Gaétan de, and Adam B Jaffe. 2018. "Econometric Evidence on the Depreciation of Innovations." *European Economic Review* 101: 625–42.

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.

Ridder, Maarten de. 2024. "Market Power and Innovation in the Intangible Economy." *American Economic Review* 114 (1): 199–251.

Romer, Paul M. 1990. "Endogenous Technological Change." *Journal of Political Economy* 98 (5, Part 2): S71–102.

Syverson, Chad. 2011. "What Determines Productivity?" *Journal of Economic Literature* 49 (2): 326–65.

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.

Appendix

Obsolescence and firm size

In this subsection, we show that allowing the obsolescence rate to depend on endogenous revenue, $\delta(R(K_t))$, does not alter the basic form of equation (9). To consider how firm size affects R&D incentives, we rewrite the Bellman equation with $\delta \equiv \delta(K_t)$ as

$$V(K_t) = \max_{K_{t+1}} \left[\Pi(K_t) - p_K\big(K_{t+1} - \big(1 - \delta(K_t)\big)K_t\big) + \frac{1}{1+r} V(K_{t+1}) \right]$$

so that the first order condition becomes

$$p_K = \frac{1}{1+r} V'(K_{t+1}) = \frac{1}{1+r} \left[\Pi'(K_{t+1}) - p_K \left(1 - \delta - \frac{d\delta}{dK} K_{t+1} \right) \right]$$

or

$$p_K \left(r + \delta + \frac{d\delta}{dK} K \right) = (1-\alpha)\beta \frac{R_i}{K_i}.$$

Taking the derivative of (8),

$$\frac{d\delta}{dK} = \frac{d\delta}{dR}\frac{dR}{dK} = -\beta\gamma \ln S \frac{r+\delta}{K}.$$

We assume that $\beta\gamma \ln S \ll 1$ so that $\ln(1 + \beta\gamma \ln S) \approx \beta\gamma \ln S$. Using this, and following the derivation in the text, R&D demand becomes

$$\ln \hat{I}_{it} = \ln R_{it} + (\beta\gamma - \mu) \cdot \operatorname{asinh} S_{it-1} + \gamma \cdot \operatorname{asinh} S_{it-1} \cdot \ln R_{it} - \ln p_K + FE + \epsilon.$$

This is the same form as equation (9) in the text, but now $\gamma_S = \beta\gamma - \mu$ instead of just $-\mu$. This means γ_S understates the direct impact of rivalry on R&D investment, however, our coefficient estimates from both the R&D elasticity regressions and regressions of (9) find $\beta\gamma \ll \mu$, so this is a secondary effect.

Regression Bias from Construction of Rivalry Measure

In the investment demand equation (9), the dependent variable, $\ln I_{it}$, is implicitly related to the rivalry measure and that can cause a bias in the coefficient estimate for S_{it}. We can see this by "partialing out" these variables, that is, using the residuals of these two variables after regressing them on other independent variables, including fixed effects and the constant term. Then the basic regression can be written in simplified form as

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

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} is our rivalry measure.

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

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

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

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

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

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

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

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

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

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:

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

since $cov(\phi_i, \log T_{t-1}) = 0$ and $\log(1 + x) \approx x$ for small *x*. The second term in the numerator, $cov(\theta_{it}, S_{it})$, 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[37]

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

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 $var\left(\overline{\frac{I_i}{T_i}}\right)/var(S_{it})$ and find that it, too, is small but positive, reducing the net negative bias further. Relative to the estimates of $\hat{\beta}$ from Table 4, the negative bias in (A4) is less than 10% except for the first period. Moreover, it is offset by the positive bias term, $cov(\theta_{it}, S_{it})$. Hence, we do not think that the net bias substantially affects our results, so we ignore it in the main paper.

[37] From (A1) and (A3), $\log I_{it} = \beta S_{it} + \phi_i + \theta_{it}$ 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 $cov\left(\overline{\left(\frac{I_i}{T_i}\right)}, \frac{I_{it-1}}{T_{it-1}}\right) = var\left(\overline{\frac{I_i}{T_i}}\right)$ so that $cov\left(\overline{\log I}, \frac{I_{it-1}}{T_{it-1}}\right) \approx cov\left(\phi_i, \frac{I_{it-1}}{T_{it-1}}\right) - \beta var\left(\overline{\frac{I_i}{T_i}}\right)$.

Table. Bias estimates

	$-\frac{cov\left(\overline{\log I_\iota}, \frac{I_{it-1}}{T_{it-1}}\right)}{var(S_{it})}$	$\frac{\overline{var\left(\frac{I_\iota}{T_\iota}\right)}}{var(S_{it})}$
1977-1991	-.22	.065
1992-1999	-.07	.054
2000-2007	-.104	.079
2008-2018	-.135	.072

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

Symmetric Nash Equilibrium

First, solve the static optimization of inputs, $\max_X(R(X) - p_X W)$ to get the optimal revenue level,

$$\hat{R} = \left(AK^{\beta}\right)^{\frac{1}{1-\alpha}}(\alpha/p_X)^{\frac{\alpha}{1-\alpha}}.$$

Substituting this into equation (6)

$$\frac{p_K}{1-\alpha}(r+\delta) = \rho = \frac{\beta\hat{R}}{K},$$

using $I = gK$ as above, and rearranging we get a modified R&D demand equation

$$\ln I = \theta\left[\frac{\ln A}{1-\alpha} + \ln\beta - \ln p_K - \ln(r+\delta) + \text{FE}\right], \quad \theta \equiv \frac{1-\alpha}{1-\alpha-\beta}.$$

We assume $\theta > 0$. Now consider a symmetric Nash equilibrium of *N* firms. Simplifying equation (8) slightly, we have

$$\ln(r+\delta) = \gamma \ln S\,, \;\; S = (N-1)I.$$

Taking the full derivative,

$$\frac{d\ln I}{d\ln\beta} = \frac{\partial \ln I}{\partial \ln\beta} + \frac{\partial \ln I}{\partial \ln S}\cdot\frac{d\ln S}{d\ln\beta} = \theta - \theta\gamma\frac{d\ln I}{d\ln\beta},$$

solving to

$$\frac{d\ln\hat{I}}{d\ln\beta} = \frac{\theta}{1+\theta\gamma} > 0.$$

As the output elasticity of R&D rises, all firms increase their R&D, raising S, and raising the obsolescence rate.

R&D Adjustment Costs and Monopsony

It is possible that rising adjustment costs or declining monopsony (rising markdown) might raise the effective price firms pay for R&D inputs, creating a "wedge" between marginal returns to R&D and marginal cost. Some evidence suggests otherwise; first, adjustment costs. Peters and Taylor (2017) show that the slope of intangible investments on Tobin's q, measured by the ratio of firm value to the sum of physical and intangible capital, slightly (but statistically insignificantly) increased from the early periods (1975-1995) to late periods (1996-2011). This implies that the firm's responsiveness to intangible investments in

Tobin's q did not decline and does not support a rise in adjustment costs. R&D is the largest component of Peters and Taylor's measure of intangible capital. Furthermore, rising adjustment costs would imply an increase in autocorrelation of R&D investments, but we find that the autocorrelation has declined from the first sample period (1977-1991) to the fourth (2008-2018). Hence, this alternative explanation is unlikely to be the case.

Another possible wedge is declining monopsony power in the acquisition of R&D inputs, including personnel. Weaker monopsony power would raise markdowns, raising marginal costs relative to observed prices paid for R&D inputs. The empirical literature on monopsony wages has used the concentration of occupational employment in geographic areas to measure monopsony (for a review see Card 2022). To explore monopsony power in R&D inputs, we constructed a Herfindahl-Hirschman index of the concentration of R&D expenditures within each state for each year and we averaged the state indices for each firm by the share of the firm's R&D in each state. We then regressed the log of firm sales to R&D against this concentration index and the mean tax cost of R&D with firm fixed effects. We find that the concentration of R&D is not statistically significantly correlated with a lower R&D intensity (higher ratio of sales to R&D) at the 5% level. We also find that the elasticity of R&D relative to the tax price has risen, suggesting that monopsony markdowns have not increased.

Supplementary Tables

Table A1. 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).

Table A2. Elasticity Regression with Markup

Period	1977-1991 (1)	1992-1999 (2)	2000-2007 (3)	2008-2018 (4)
Dependent variable: Log R&D				
Log R&D Stock	0.0052***	0.0048***	0.0072***	0.0126***
	(0.0002)	(0.0003)	(0.0004)	(0.0003)
Markup (Raval method)	0.3152***	0.3027***	0.2517***	0.2536***
	(0.0009)	(0.0010)	(0.0008)	(0.0006)
Adjusted R^2	0.653	0.684	0.688	0.715
Observations	263000	144000	128000	196000

Note: Standard errors are shown in parentheses and are clustered by firm (*** p<0.01, ** p<0.05, * p<0.10). All regressions have year and 6-digit NAICS fixed effects and use adjusted sample weights. The Levinsohn-Petrin TFP estimates used separate regressions for each 3-digit NAICS industry. The R&D stock is calculated using an estimated time-varying obsolescence rate. Markup is calculated using the Raval method for intermediate inputs for each establishment. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY26-P2735-R12846).

Table A3. First Stage Regression for R&D Instrument

	Log R&D
Log theta	-1.404***
	(0.174)
Adjusted R^2	0.971
Observations	196,000
Fixed Effects	Year, firm
F Test	65.04
Period	1977-2017

Note: Standard errors are shown in parentheses and are clustered by firm (*** p<0.01, ** p<0.05, * p<0.10). The variable theta indicates the tax price of R&D, computed as one minus the effective rate of R&D tax credit. The number of observations is rounded to protect confidentiality. Regression uses adjusted sample weights. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155). The effective tax rate is calculated following Arque-Castells and Spulber (2022), Appendix G, equation (A11). For this instrument, used in Table 1, we only use the Federal tax credit in constructing the instrument. State level R&D data are not available for every year before 1997. Since we want a consistent time series from 1976, we only use the Federal tax credit data here. It is nevertheless a strong instrument (F test 65.04). Below, we use Federal and state R&D tax credit for the instrument used in Table A7.

Table A4. Elasticity with respect to R&D, Production Function Estimates, OLS

	(1)	(2)	(3)	(4)
Dependent variable: Log Real Output				
Log labor	0.282***	0.258***	0.286***	0.300***
	(0.003)	(0.002)	(0.002)	(0.005)
Log intermediates	0.593***	0.609***	0.598***	0.564***
	(0.003)	(0.002)	(0.003)	(0.005)
Log capital	0.110***	0.116***	0.101***	0.082***
	(0.002)	(0.002)	(0.002)	(0.005)
1977-1991 x Log $R\&D_{t-1}$	0.009***	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
1992-1999 x Log $R\&D_{t-1}$	0.014***	0.003	0.001	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)
2000-2007 x Log $R\&D_{t-1}$	0.016***	0.007***	0.007***	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
2008-2018 x Log $R\&D_{t-1}$	0.023***	0.011***	0.014***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Adjusted R^2	0.932	0.925	0.943	0.968
Observations	672,000	672,000	672,000	672,000
Fixed effects	Industry, year	Firm, year	Industry x year, firm	Establishment, year

Note: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Regressions cover establishments from 1977 to 2018 and use adjusted sample weights. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

The dependent variable is the log of real output instead of the estimated TFP, and independent variables include labor, intermediate inputs, and physical capital at the establishment level. In the first column, we examine the relationship between R&D expenditures and output with a one-year time lag, while controlling for year and detailed industry fixed effects as in Table 1. All observations from 1977 to 2018 are pooled in this analysis. The estimated elasticity increases from 0.009 in the first sample period to 0.023 in the fourth sample period, shown in the interaction terms between R&D expenditures and sample period dummies. The results here are quantitatively similar to the results in Table 1, showing the robustness of the findings. From the second to the fourth column, regressions with various fixed effects are explored. In the second column, firm and year fixed effects are absorbed to control for unobserved firm characteristics. As expected, the coefficients on lagged R&D expenditures attenuate due to the inclusion of more granular fixed effects, but the trend remains robust. The regression in the third column controls for firm fixed effects and year times industry fixed effects to account for time-variant industry-specific shocks. Finally, the fourth column shows the regression results with year and establishment fixed effects to control for unobserved establishment characteristics.

Table A5. Elasticity with respect to R&D from Compustat Panel

Dependent variable: Log Real Sales		
Log labor	0.302***	0.132***
	(0.010)	(0.008)
Log intermediates	0.347***	0.551***
	(0.009)	(0.012)
Log Capital	0.291***	0.193***
	(0.016)	(0.016)
1977-1991 x Log $R\&D_{t-1}$	0.025***	0.070***
	(0.003)	(0.006)
1992-1999 x Log $R\&D_{t-1}$	0.050***	0.086***
	(0.003)	(0.006)
2000-2007 x Log $R\&D_{t-1}$	0.069***	0.092***
	(0.004)	(0.006)
2008-2018 x Log $R\&D_{t-1}$	0.074***	0.089***
	(0.004)	(0.006)
Adjusted R^2	0.981	0.994
Observations	8727	8727
Fixed effects	--	Firm, year

Note: Robust standard errors are shown in parentheses (*** p<0.01, ** p<0.05, * p<0.10). Panel from 1976 to 2018 of firms that reported in both the first and last years of the panel. Intermediates are calculated as xopr - dp – xstf; if personnel costs are not reported, we impute them from industry compensation; if operating expense is not reported, we use cogs + xsga.

Table A6. R&D Investment with Instrument for Log Sales

Period	1977-1991 (1)	1992-1999 (2)	2000-2007 (3)	2008-2018 (4)
Dependent variable: Log R&D				
Asinh(rival $R\&D_{t-1}$)	-0.258	-0.641**	-1.067***	-1.283***
	(0.474)	(0.257)	(0.369)	(0.298)
Log(pred. revenue) x asinh(rival $R\&D_{t-1}$)	-0.007	0.009	0.025	0.052**
	(0.048)	(0.019)	(0.027)	(0.023)
Log(pred. revenue)	0.805***	0.851***	0.762***	0.614***
	(0.149)	(0.043)	(0.051)	(0.042)
Adjusted R^2	0.646	0.737	0.705	0.624
Observations	25000	19500	28500	48500

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. Predicted revenue is obtained from a regression of log revenue on year and a firm fixed effect. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

Table A7. R&D Investment with Instruments for Log Sales and for Rivals' R&D

Period	2000-2007	2008-2018
	(1)	(2)
Asinh(pred. rival $R\&D_{t-1}$)	-0.910***	-1.325***
	(0.256)	(0.271)
Log(pred. revenue) x asinh(pred. rival $R\&D_{t-1}$)	0.0239	0.0600***
	(0.0181)	(0.0200)
Log(pred. revenue)	0.763***	0.587***
	(0.0380)	(0.0426)
Adjusted R^2	0.726	0.651
Observations	25000	41500

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. Predicted revenue is obtained from a regression of log revenue on firm age, year, and a firm fixed effect. Predicted rivals' R&D is obtained by regressing log R&D against log R&D tax cost and a firm fixed effect, obtaining the prediction, and calculating the weighted sum as in the base measure of rivals' R&D. Here, state-level R&D tax price data are used and are not available for all years prior to 2000. The number of observations is rounded to protect confidentiality. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

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 $\rho_{it} P^{R\&D}_t (r_t + \delta)$, where $P^{R\&D}_t$ 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 cost is a reasonably good predictor of R&D, so the first stage regression is strong (F-test statistic 356.7).

Following the literature, we use this instrument to predict rivals' investment, and we then use these predicted values to calculate S in the IV estimates in Table A7. Note that state level R&D data are only available for our last two periods. In Bessen and Wang (2024), we tested alternative instruments, including one that omitted rivals in the same state as the focal firm (lest the instruments be correlated with the focal firm). Results were highly similar.

Table A8. R&D Investment and Technological Rivalry, Additional controls

Period	1977-1991 (1)	1992-1999 (2)	2000-2007 (3)	2008-2018 (4)
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) x asinh(rival $R\&D_{t-1}$)	0.100***	0.041**	0.04	0.147***
	(0.031)	(0.018)	(0.026)	(0.026)
Foreign = 0 x log(revenue)	0.491***	0.664***	0.627***	
	(0.117)	(0.051)	(0.059)	
Foreign = 1 x 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	17000	11000	14000	20000

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 A9. Industry dynamism and technological rivalry

Using 6-digit NAICS industry cross-sectional observations, the table regresses dynamism measures 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.

Naics6 industry means, 2003-2018

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

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

Table A10. 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

Notes: The technological rivalry measure (X) is computed at the firm level and then averaged within each NAICS four-digit industry. The table reports the ten industries with the highest technological rivalry. The sample period spans 1976 to 2018.