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May 2025

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Ideas are not getting harder to find

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April 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 (TFP) with respect to R&D and the marginal returns to R&D have risen sharply. Exploring factors affecting returns, we conclude that R&D obsolescence rates must have risen. Using a novel estimation approach, we find consistent evidence of sharply rising technological rivalry. These findings suggest that R&D has become more effective at finding productivity-enhancing ideas but these ideas may also render rivals' technologies obsolete, making innovations more transient.

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

Thanks to Holden Diethorn for providing data on tax costs. This work was supported in part through a grant from 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, and CBDRB-FY25-P2735-R12336).

1. Introduction

In Romer's 1990 growth model, the aggregate growth rate is proportional to the number of R&D researchers. R&D generates new, non-rivalrous "ideas" that are shared across the economy, multiplying output. But economists soon noted that while R&D has grown rapidly, both in absolute terms and relative to value added (see Figure 1), productivity growth and patents have not risen similarly (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) argue that the reason for this breakdown is that R&D has become less effective, that "ideas are getting harder to find." They develop a measure of research productivity motivated by the endogenous growth literature and find that their measure declines 5 percent per year for the aggregate economy and 8-10 percent per year for private firms.

These arguments evoke a pessimistic outlook where R&D can no longer overcome stagnant productivity. But where is the evidence of firms' reactions? If firm research productivity is truly declining 8-10 percent per year, then one would expect corporate managers to take notice. Yet there is little evidence of such a reaction. While declines in research productivity have been discussed in specific areas such as novel drug development (Fernald et al. 2024), general publications such as *R&D World* and *R&D Management* remain largely silent on the subject. More formally, a sharp decline in research productivity should lead to a decline in real R&D, all else equal; this follows both from endogenous growth models (e.g., Romer 1990; Aghion and Howitt 1992) and the knowledge production function model used in the empirical literature (see below). However, as Figure 1 shows, real R&D in the US has *grown* significantly over recent decades. This growth in R&D investment seems at odds with the notion of declining research productivity.

This paper explores the link between R&D investment and productivity at the micro level to gain insight about this puzzle. Using comprehensive micro-data from the US Census, we estimate time trends in the elasticity of output with respect to R&D and in the returns to R&D in the US manufacturing sector from 1976 to 2018. We focus on manufacturing because productivity is reasonably well-measured in this sector. A large literature measures both the output elasticity to R&D and the returns to R&D (for a review see Hall, Mairesse, and Mohnen 2010). We add to this literature by estimating how these measures have changed over four decades, and we make these estimates on a comprehensive sample of R&D-performing firms and establishments that includes many small firms.

We begin by estimating the elasticity and returns to firm R&D with the widely applied "knowledge production function" (Griliches 1979; Hall, Mairesse, and Mohnen 2010). Using a variety of empirical methods from the literature, including instrumental variables, we find robust evidence that the output elasticity with respect to R&D has risen substantially since 1976. In this framework, R&D has grown *more* effective at raising productivity, not less. Rising output elasticity aligns with the observed rising share of R&D in value added. To explore factors affecting the rise in output elasticity, we analyze sources of heterogeneity, including firm age, size, market position, export activity, and digitalization. We find higher output elasticities among market leaders in each industry and firms in digital-intensive sectors, whereas the output elasticity is lower among young and small firms.

We also estimate marginal returns to R&D, which are calculated as the output elasticity times the ratio of output to the R&D capital stock. The measure of the R&D capital stock depends on the assumed "depreciation" or obsolescence rate.[1] Since R&D obsolescence rates are not well measured (See overview in Mead and others 2007), we follow the literature and calculate the returns to R&D over a variety of assumed obsolescence rates. Across depreciation rates ranging from 10 percent to 30 percent, we find that the marginal returns to R&D have doubled since the 1970s. Overall, micro-level evidence suggests that the elasticity of output with respect to R&D and the returns to R&D have increased over the last four decades, in contrast to the hypothesis of declining research productivity.

How can we account for such a large rise in returns? The rise in output elasticity, while also large, does not explain it. In equilibrium, we expect the marginal return to R&D to equal the marginal cost. If the marginal cost of R&D remained unchanged, in equilibrium rising output elasticity would not change marginal returns; it would simply raise R&D relative to output. It is possible that frictions or adjustment costs might distort the equilibrium. We examine evidence of two frictions, monopsony in R&D inputs and intangible adjustment costs; we conclude that these do not account for a doubling of returns.

[1] It also depends on the choice of which moment to use to capture the ratio of output to R&D capital, which has a highly skewed distribution. As discussed below, we use a geometric mean, but we are concerned mainly with the trend in returns over time, not the particular level of returns.

We are left with examining the components of the user cost of R&D capital stock: the real interest rate, the after-tax cost of R&D, and the depreciation or obsolescence of R&D. Among these three, interest rates and after-tax costs of R&D have gone down, implying that obsolescence rates must have gone up substantially.

Indeed, if R&D has become more effective, then firms might very well become more effective as technology rivals, leading to higher obsolescence. It is quite common for firms to drop R&D in the face of superior innovations from rivals. Nokia dropped its low-end smartphone development in the face of superior products from Apple and Google; Toyota dropped its R&D on battery electric vehicles in the faces of successful rivals. Even when superior products cannot yet be identified, rivals' R&D can indicate possible obsolescence risk. Visicalc's personal computer spreadsheet program, introduced in 1979, faced over 18 rivals developing new features as they sought to capture market share. No one knew which features were key until 1983 when Lotus Development introduced a "dominant design" that soon replaced Visicalc's market leadership.

We hypothesize and test the notion that rivals' R&D increases a firm's *expected* obsolescence risk, hence reducing expected returns to innovation, and, all else equal, reducing R&D investment. Below we build a model that combines R&D capital assets with the Grossman and Helpman (1991) model of firm rivalry and replacement where we treat the obsolescence rate as a function of rivals' R&D. Our approach differs from much of the large IO literature on technological rivalry (see review by Reinganum 1989). We are concerned with technological rivalry that cannot necessarily be reduced to a race over a single, commonly known innovation, and we treat R&D as a long-lived asset (capital stock) so that rivals' current spending may affect future obsolescence risk.[2]

The model predicts that firm R&D varies with rivals' R&D because of obsolescence risks. In prior research (Bessen and Wang 2024), we found that firms significantly reduce their own R&D as rivals invest more. Extending this analysis to our entire sample, we infer that technological rivalry has risen sharply since 1990. Using a novel method, we infer lower-bound obsolescence rates from the rivalry measure. These, too, have increased sharply and this rise can account for the rise in the returns to R&D.

[2] As Doraszelski (2003) notes, in most of the literature, R&D is "memoryless".

While many papers estimate elasticities and returns to R&D (see review in Hall, Mairesse, and Mohnen 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. This 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.

To summarize, using comprehensive data for manufacturing from 1976-2018, we find inter-related trends in R&D activity that portray a transformation in the nature of research activity that has not been recognized in the literature. Over the last three or four decades we find that both the elasticity of output with respect to R&D and the marginal returns to R&D have increased substantially. Not surprisingly, investment in R&D has gone up along with technological rivalry stemming from this investment. Furthermore, the large rise in marginal returns suggests a large rise in R&D obsolescence rates. Estimates of obsolescence based on the rising rivalry measure confirm such a rise. Understanding the changing nature of R&D is important for R&D policy and, more generally, for understanding the role of R&D in productivity growth.

2. R&D Model

We begin by using a standard "knowledge production function" equation (Griliches 1979; for a review see Hall, Mairesse, and Mohnen 2010) to estimate the elasticity of output with respect to R&D,

$$\ln R = \alpha \ln X + \beta \ln K + \ln A + \epsilon \tag{1a}$$

where R is deflated firm revenue, X is a composite of input factors (labor, physical capital, and intermediate inputs), K is the firm R&D stock (defined below), and A captures other sources of productivity, spillovers from other firms, knowledge gained from learning-by-doing, and the quality of researchers. We assume $\alpha < 1$ to capture diminishing returns to scale and/or markups; β is the revenue elasticity with respect to R&D that we seek to estimate. Alternatively, we use the equivalent total factor productivity form

$$\ln TFP = \beta \ln K + FE + \epsilon, \quad \text{where } \ln TFP \equiv \ln R - \alpha \ln X. \qquad (1b)$$

We estimate total factor productivity using structural methods (Levinsohn and Petrin 2003).

In the knowledge production function, R&D improves firm productivity by creating new products and by creating products of higher quality or profitability. The knowledge stock represents the accumulated knowledge accrued from the sequence of past R&D investments. But some of the new products created become obsolete as rival firms replace them with superior products. In this case, some of the firm's knowledge becomes obsolete, that is, it is no longer commercially valuable. To capture the effect of obsolescence on the knowledge stock and hence on productivity, we follow the literature and construct R&D capital stocks using the perpetual inventory method with an obsolescence rate, δ, and R&D investment I_t,

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

Some sources refer to δ as "depreciation" by analogy to physical capital. We prefer the term obsolescence because knowledge derived from R&D does not "wear out," but it becomes obsolete as R&D-based products lose commercial value when they are replaced by rivals' products. Below we specifically model how interfirm rivalry leads to replacement/obsolescence.

To estimate elasticities of output with respect to R&D, we sometimes use lagged R&D expenditure in lieu of the R&D capital stock. In the Appendix we show that estimates of elasticity obtained using lagged R&D expenditure are approximately the same as estimates obtained using R&D capital stocks, when the R&D growth rate, g, is approximately constant. This holds both in theory and practice.[3]

However, estimates of the *returns* to R&D do depend on the obsolescence rate and the resulting level of capital stock. That is, the gross marginal return to R&D is

$$\rho \equiv \frac{\partial R}{\partial K} = \beta \frac{R}{K}. \qquad (3)$$

For a given elasticity, β, the returns depend on the choice of obsolescence rate used to construct K. In our empirical analysis, we first show returns using a variety of different

[3] Generally, researchers find that estimates of R&D elasticity are insensitive to changes in the obsolescence rate (Griliches and Mairesse 1984; Bernstein 1998; Bernstein and Nadiri 1988; Hall and Mairesse 1995; Harhoff 1998).

obsolescence rates. Then we estimate obsolescence rates from the data and consider how these might affect returns.

To explore the role of obsolescence for innovation, we draw on an influential model of replacement by Grossman and Helpman (1991). We embed the knowledge production function in this model and use it to explore how interfirm competition affects R&D. In this model, the risk of replacement arises from a wide range of innovators, including rival firms that are not current competitors in the same product markets. This is appropriate for our exploration of R&D returns in a broad sample of firms. We assume that the firm optimizes its profit, taking rivals' R&D and the obsolescence rate as a given.

As the Grossman and Helpman model is well-known, we briefly sketch the standard features here and refer the reader to the underlying paper for further details. Let the economy consist of a unit continuum of differentiated products; the number of these products are fixed. Consumers have Cobb Douglas preferences over these goods, so they spend an equal amount, E, on each. Consumers have constant time preferences so that there is a constant discount rate, $r > 0$.

Multiple firms potentially compete in the product market for each good, but their offerings differ in quality. Innovation takes the structure of a "quality ladder" where innovating firm *i* introduces a product version of good *j* that has a quality that is $\lambda_i > 1$ greater than the previous quality leader. This "inventive step" differs across firms, capturing heterogeneous development capabilities, learning-by-doing and other differences.

One unit of labor is needed to produce each unit of output, so the marginal cost is the wage rate, w. We assume the innovations are non-drastic and the new leader and the incumbent engage in Bertrand competition (there is no licensing), driving prices down until the incumbent earns no profits. This occurs when the entrant charges a limit price $p_i = \lambda_i w$, driving the incumbent out of the market. Then demand is E/p_i and the flow of profits is $\pi_i = (p_i - w)\, E/p_i = \left(1 - {}^{1}/_{\lambda_i}\right) E$. This process of replacement is what drives obsolescence and determines the obsolescence rate.

Firm *i* can have $n_i \geq 1$ products so that firm profits are

$$\Pi_i = n_i \pi_i.$$

Firm R&D plays a role in adding new products (increase n_i) and increasing their profitability, π_i. Without specifying the exact mechanisms by which R&D affects both margins, we can use the knowledge production function to derive a profit function $\Pi_i = \Pi_i(K_i)$ where (see Appendix)

$$\Pi_i'(K_i) = \beta \frac{R_i}{K_i}. \tag{4}$$

With this profit function, we can write the Bellman equation for the value of the firm (suppressing the firm subscript), taking the expected obsolescence rate, δ, as given,

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

where 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. The discount rate is r. For the moment, take δ as fixed, given rivals' R&D.[4]

The first order maximizing condition gives us

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

where the second expression comes from recursive use of the Bellman equation. Using (3) and (4), rearranging and assuming the optimal policy is followed all years, we get

$$p_K(r+\delta) = \beta \frac{R_i}{K_i} \equiv \rho. \tag{6}$$

This is of the same form as Jorgenson's user cost for depreciating physical capital (Jorgenson 1963). Assuming an approximately constant growth path, $I = gK$, we can write an investment demand equation with fixed effects

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

This is the firm's reaction function given δ.[5]

To implement an empirical analysis using this equation, we need to specify obsolescence as a function of rivals' R&D. In the model, the more that rival firms invest in R&D, the more frequently they will come up with innovations that replace products of the focal firm. But realistic empirical analysis requires several additional considerations that go beyond the base model:

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[4] In the appendix we consider $\delta(S, R(K))$.

[5] In this paper the reaction function is sufficient for our purposes. In Bessen and Wang (2024) we explore a Nash equilibrium in a closely related model.

- Only *some* firms are likely to develop replacement products; we don't expect software firms to replace steel products. 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.
- Many firms do not invest in R&D and some narrowly defined industries will have very little aggregate R&D. This pattern may arise from fixed costs of performing R&D, but our empirical specification needs to accommodate it.
- Firm size might affect the rate of obsolescence. For instance, firms with many products may establish a reputation among a loyal customer base. When a superior replacement arrives for one product, consumers may be slow to switch, reducing the effective obsolescence rate.

With these considerations in mind, we specify a lower-bound obsolescence rate[6]

$$\ln(r+\delta_{it}) = \ln r + (\mu - \gamma \ln R_{it}) \ln S_{it-1} \quad \text{or} \quad \delta_{it} = r\left(S_{it-1}^{\mu-\gamma \ln R_{it}} - 1\right) \qquad (8)$$

where S is a measure of industry rivals' R&D and μ and γ are parameters to be estimated. Inserting this into equation (7) and replacing $\ln S$ with $\operatorname{asinh} S$ to accommodate small or zero R&D cases, we get a flexible form

$$\ln I_{it} \approx \gamma_t + \gamma_j + \gamma_S \cdot \operatorname{asinh} S_{it-1} + \gamma_x \cdot \operatorname{asinh} S_{it-1} \cdot \ln R_{it} + \gamma_R \cdot \ln R_{it} + \epsilon_{it} \qquad (9)$$

Where $\gamma_S = -\mu, \gamma_x = \gamma, \gamma_j$ is an industry fixed effect and γ_t is a year dummy. This is the base regression we run below. Coefficient γ_S provides a simple measure of the direct impact of rivals' R&D. To the extent that there are positive knowledge spillovers from rivals' R&D this coefficient is net of that effect; spillovers are also captured in γ_R. This derivation has glossed over a potentially important second order concern: because larger firm size may decrease a firm's obsolescence rate, firms have an additional incentive to invest in R&D to increase firm size. In the Appendix we show that taking this effect into account does not

[6] This is a lower bound obsolescence rate because it only includes obsolescence caused by rivals' innovation. In some cases, products become obsolete for exogenous reasons. For example, microbes become resistant to antibiotics.

change the form of equation (9) but slightly changes the interpretation of coefficient γ_S. Moreover, our estimates find that this effect is secondary.

Using the coefficient estimates and sample means (indicated by overbars), we can estimate the obsolescence rate in (8),[7]

$$\hat{\delta}_t = r\left(e^{\hat{\gamma}_S \cdot \overline{\text{asinh}\, S_{it-1}} + \hat{\gamma}_x \cdot \overline{\text{asinh}\, S_{it-1}} \cdot \overline{\ln R_{it}}} - 1\right). \tag{10}$$

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.[8] 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

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[7] This calculation slightly understates the obsolescence rate to the extent that $\hat{\gamma}_S > -\mu$. See Appendix.

[8] 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.

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.[9] 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

Our main regression to estimate the output elasticity is given by equation (1b). To implement this, we construct the measure of establishment-level TFP as follows:

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

The data on revenue and three production inputs at the establishment level are drawn from the ASM, CM, and LBD. The three coefficients in the production function (i.e., $\beta_{\text{labor}}, \beta_{\text{capital}}, \beta_{\text{int}}$) are estimated by the control function approach, pioneered by Olley and Pakes (1996). Since firms endogenously choose production inputs in response to

[9] 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.

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 prodcutivity shock.[10] The estimation is implemented by the prodest Stata package. We specify labor as a free variable, capital as a state variable, and intermediate inputs as a proxy variable. Furthermore, we estimate the production function at each NAICS 3-digit industry, as the nature of production funcation may differ across industries. 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.

In the regression equation (1b), we examine the relation between productivity at the establishment level and R&D at the firm level. This specification assumes that technologies are perfectly transferred across a firm's establishments. This assumption is theoretically plausible, as it is optimal for firms to share their knowledge and technologies in all of their production facilities. Still, Adams and Jaffe (1996) suggest that knowledge spillovers within firms may be imperfect due to transfer costs. To account for this, we run an additional regression that includes the log of the number of establishments within a firm as a control variable, allowing for an imperfect knowledge transfer across establishments. Note that R&D expenditures are reported at the firm level in the SIRD and BRDIS datasets, while revenue and production inputs are recorded at the establishment level. Rather than aggregating establishment-level variables for a firm-level analysis, we maintain this distinction, as establishments within the same firm may operate in different NAICS 3-digit industries or even outside the manufacturing sector. This approach ensures that our TFP measure captures industry-specific heterogeneity in the production function.

Another concern in the estimation of regression equation (1b) is a potential correlation between the error term and R&D expenditures, as firms may adjust R&D

[10] 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).

expenditures in response to productivity shocks. To mitigate this concern, we take a lag in R&D expenditures and examine the relation between R&D and productivity with a one-year time lag. Also, note that we are mainly interested in the change in the output elasticities over time. The potential endogeneity would not alter the main finding on the time trend unless the degree of endogeneity has changed over time. Furthermore, we 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 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. We then use the predicted R&D instead of actual R&D as an independent variable in the regression (1b). A similar approach is adopted by Bloom et al. (2013) and Arque-Castells and Spulber (2022).

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.

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.

We construct a lagged measure of rivals' R&D for firms in industry J as $S_{it-1} \equiv \sum_{\substack{j \neq i \\ j \in J}} I_{j,t-1}$ 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 with similar results.

4. Empirical Findings

Revenue elasticity trends

Table 1 shows the estimates of output elasticity with respect to R&D expenditures in four sample periods. The baseline results in Panel A show that the elasticity has increased over time: 0.010 in the first sample period (1977-1991), 0.010 in the second (1992-1999), 0.013 in the third (2000-2009), and 0.019 in the fourth (2008-2018). These coefficients mean that doubling R&D expenditures is associated with a roughly 1% increase in TFP in the next period. In Table 1, year fixed effects and detailed industry (NAICS 6-digit code) fixed effects are absorbed. Therefore, we exploit within-industry variations across firms and over time. While firm fixed effects could further control for unobserved firm characteristics, they would absorb most of the variation, given the persistence of R&D expenditures. Instead, we assess the robustness of the results with various fixed effects, including firm and establishment fixed effects, in Table 2. To conduct consistent analysis across different sample periods, observations are weighted by our adjusted sample weights.[11] The sample

[11] 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

weights also make the sample representative of US firms. The number of observations is over 100 thousand in each sample period and is significantly larger than the sample of publicly traded firms.

Panel B uses the predicted R&D based on R&D tax credit 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. Here, the coefficient of 0.01 means that doubling predicted R&D investments, calculated using the tax price of R&D, is associated with a roughly 1% increase in TFP in the next period. The similar coefficients in Panel B suggest that firms' endogenous response in their R&D to future productivity shocks may not be a significant concern. Panel C checks the robustness of the results using R&D stocks constructed by the perpetual inventory method (equation 2) as the independent variable. Using the stock variable instead of flow R&D expenditures does not significantly alter the results. Panel D 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 in all establishments within the firm. Controlling for the number of establishments accounts for the possibility of imperfect technology transfers across establishments within each firm. The rise in elasticities is robust to this specification, while the additional control variable is not statistically significant except for the first sample period. Finally, Panel E 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 expenditure shares of corresponding inputs within each 6-digit NAICS industry. Again, we see an increase in elasticities over four sample periods.

Table 2 examines the trend in output elasticity to R&D expenditures in a different specification. 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

these results are released from the Census Bureau (Approval Number: CBDRB-FY25-P2735-R12336) to minimize the volume of output and reduce disclosure risk.

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. Under these regression specifications, the elasticity estimates for the first sample period become statistically insignificant, but the estimated elasticity exhibits a substantial increase over time. For instance, the estimated elasticity in the fourth column increases from 0.001 in the first sample period to 0.010 in the fourth sample period. These results show the robustness of the increase in output elasticities. As a further robustness check, we conduct a similar regression using a balanced panel of Compustat firms in the Appendix (Table A3). Despite major differences in samples, this analysis also finds significantly rising output elasticities.

Heterogeneity analysis

Table 3 explores the heterogeneity in output elasticities 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. In particular, the interaction term for young firms is similar in magnitude to the base term (0.009), implying that their output elasticity is statistically insignificant. In contrast, the elasticity estimates are larger among firms that operate in digital-intensive industries, measured by computer expenditures per capita, 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 to R&D. Note that both output and R&D used in the regression are measured in domestic markets. 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.

Trend of marginal returns to R&D

Table 4 reports the estimated returns to R&D, which depend on the assumed obsolescence rate of R&D stocks. We present estimates with various obsolescence rates, ranging from 10% to 30%. We first estimate the output elasticity to R&D stocks, as in Table 1-C, with a particular obsolescence rate, and then compute the returns to R&D, following equation (3). The table reports the geometric mean of the estimated returns. With the commonly used 15% obsolescence rate, the estimated returns increase from 8.8% in the first sample period (1977-1991) to 23.5% in the fourth (2008-2018). Higher obsolescence rates lead to higher estimated returns, as the ratio of output to R&D stocks rises. With the obsolescence rate of 30%, the returns increase from 16.0% in the first sample period to 48.3% in the fourth sample period. While the level of returns varies with assumed obsolescence rates, all specifications in the table show that the returns to R&D have substantially increased over time, doubling or tripling.

Why have returns risen?

Inspecting equation (3), R&D returns consist of two components: the elasticity of output with respect to R&D and the R&D intensity, that is, the ratio of R&D (stock or flow) to firm sales. Our evidence shows that the output elasticity has risen sharply, tending to increase returns, but the R&D intensity has also risen in aggregate (see Figure 1), tending to dampen this rise. The growth in R&D elasticity can be broadly understood as a change in the technology of R&D or in the nature of the technological opportunities open to firms. But, given the output elasticity of R&D, the returns to R&D represent an economic decision of the firm. Presumably firms invest in R&D until the returns equal the marginal cost. In equilibrium, R&D returns should equal the user cost of R&D capital as defined in equation (6).

To explore the factors contributing to a rise in R&D returns, we look at the components of the user cost of R&D capital. We also look at possible reasons that a "wedge" might arise between returns and marginal cost of R&D. Consider the components of user cost: the price of R&D, 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.[12] In any case, the R&D deflator closely tracks the GDP deflator. Since the majority of R&D expenditure consists of personnel costs, we can also look at the relative wages of scientists and engineers in private industry to the wages of other occupations. 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%. Finally, the after-tax cost of R&D has declined as the Federal government and states have offered increasingly generous tax treatment of R&D (Barth et al. 2023). 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.

Nor can interest rates account for the doubling; interest rates fallen substantially. For instance, real 10-year Treasury yields have fallen from 6.9% in 1982 to 1.2% in 2018.[13] 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.[14]

What about rising "wedges" between R&D investment and marginal cost? One possibility is rising adjustment costs. However, 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

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

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

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

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 rising monopsony power in the acquisition of R&D inputs, including personnel. A rising markdown would mean that marginal costs rose 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. Moreover, the geographic concentration of R&D has declined over our analysis period. We also find that the elasticity of R&D relative to the tax price has risen, suggesting that monopsony markdowns have not increased.

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. There is, in fact, good reason to expect rising obsolescence. The rising effectiveness of R&D at generating firm productivity might well involve greater effectiveness at competing with rivals. We explore this possibility next by measuring the relationship between rivals' R&D and own-firm investment in R&D.

Measuring Technological Rivalry

Previous work finds rivals' R&D is associated with substantially reduced firm R&D investment all else equal (Bessen and Wang 2024).[15] While spillovers from other firms' R&D

[15] 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).

(not necessarily rival firms) provide a benefit to firms, especially large firms, the evidence shows a substantial negative relation between rival firms' R&D and focal firm's R&D on average. 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 5 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. To proxy for the size of the customer base, we use the log of real net sales. 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.[16]

The coefficients of rivals' investment, shown in the first row, are negative, meaning that rival firms' R&D in the last period is negatively associated with focal firms' R&D; and the magnitude increases substantially over time.[17] We also test for industry variation but find no statistically significant differences.[18]

There are several possible concerns with this finding. One is that the estimates may be contaminated by the inclusion of the sales measure which is endogenous. To address this concern, Panel A of Table 6 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. In the Appendix Table A4, we also show the full regression, but we instrument the sales variable. To obtain predicted sales, we regress firm log sales on firm age and a firm fixed effect. Using this predicted sales variable, we again obtain significant coefficients on rivals' R&D that increase substantially over time although they are a bit lower than the coefficients in Table 5.

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

[17] Note that the coefficient on the interaction between revenue and rivals' R&D is positive. This means that the combined effect of rivals' R&D, the net externality, is positive for some large firms (capturing spillovers). See Bessen & Wang (2024 p. 22).

[18] 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.

Another concern is that rivals' R&D might be correlated with third factors that affect firm R&D. One possibility is that both the focal firm and rival firms may respond to common shocks, tending to bias the coefficients upwards. Another concern is that rivals' R&D might be correlated with other characteristics of rival firms that affect focal firm investment rather than the rivals' R&D itself. 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 6 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.[19] The significant coefficients on these control variables suggest that market competition affects R&D investment. For example, larger market share (smaller rivals' market share) is strongly associated with greater R&D. 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 (not shown) with controls for a variety of IO competition concerns.[20] All of these specification still showed a statistically significant increase in the (negative) coefficient on rivals' R&D. Finally, 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. Table A5 in the Appendix 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]

[19] 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).

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

[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.

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 replace focal firm innovations, making them 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 make a difference, 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, Schankerman, and Van Reenen 2013) or might even increase it (W. M. 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, as above, we do not see a rise in the wage premiums of these occupations. Perhaps these labor markets are monopsonistic, constraining wage effects. But the rivalry we are concerned about occurs nationally while labor market competition is substantially local. Moreover, above we found only weak monopsonistic effects.

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.

Estimating obsolescence rates

Equation (10) provides a method to estimate a lower-bound obsolescence rate based on the regression used in Table 5. 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 bottom panel of Table 4 shows estimates of these obsolescence rates with bootstrapped standard errors.

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.[22] Huang and Diewert (2011) estimate rates for US manufacturing industries from 1953-2000 ranging from 1 percent to 29 percent overall.[23] 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.

The last column of Table 4 shows the change in returns and lower-bound obsolescence rates from the first period to the last. The increase in returns to R&D ranges from 10% to 32%; obsolescence rates increased 19%, putting it right in the middle. Thus, rising obsolescence, stemming from growing technological rivalry, provides a plausible explanation for the rise in the returns to R&D. Moreover, it means that while gross marginal returns to R&D have risen sharply, *net* marginal returns—gross returns minus obsolescence—may have remained stable.

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. Moreover, the rise in the revenue elasticity with respect to R&D reflects a broader shift in the nature and direction of industrial research: gross marginal returns have increased sharply, R&D intensity has grown substantially, technological rivalry has intensified, and obsolescence rates have doubled.

Of course, R&D may become less productive in narrow technical areas as they are "fished out"; e.g., the growth in number of transistors on a CPU chip slows as designs bump up against physical limits. But our evidence implies that firm generation of productive ideas has not slowed overall. Bloom et al. (2020) show ample evidence that their measure of research productivity—the ratio of productivity growth to real R&D—has declined. Yet this measure is drawn from growth models such as Romer (1990). Notably these models do not

[22] Including outliers, the estimates range from -11 percent to 100 percent.

[23] De Rassenfosse and Jaffe (2018) use surveys of Australian inventors with patented inventions to estimate that inventions lose value at 2-7 percent per year. However, invention depreciation rates are not directly comparable to R&D depreciation rates and their survey had low responses because they could not find addresses for most inventors. It seems likely that inventors of obsolete inventions might be far more likely to lack an address.

consider obsolescence or do not consider growing obsolescence. When obsolescence is rising, their measure does not reflect real research productivity (see Ando and Bessen 2025).

Nevertheless, Bloom et al. highlight an important puzzle: while industrial research appears to have become more effective at generating returns for individual firms, aggregate productivity has grown little. While it seems that innovative "ideas" are *not* harder to find, it may be harder to translate them into aggregate productivity growth. Fort et al. (2025), looking at firm growth rates, make a similar point. One reason may be the changing nature of R&D. Rising obsolescence implies that more R&D is effectively directed to replacing existing products rather than to developing new ones; it also implies a shorter average life for innovations. As a result, while gross marginal returns to R&D have more than doubled, net marginal returns may not have. In a related paper, we explore the possible significance of rising obsolescence in a growth model; we argue that rising obsolescence can decrease aggregate productivity growth for a time even when research productivity has not declined (Ando and Bessen 2025). While the replacement of products by superior versions increases productivity at the micro level, an overall rise in the rate of replacement can have a significantly negative effect on the aggregate productivity growth rate.

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$_{t-1}$	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
Observations	260,000	138,000	123,000	162,000
B. 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
C. Dependent variable: Log TFP (Levinsohn-Petrin), OLS				
Log R&D stock	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
D. 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
E. 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 E uses TFP calculations based on cost shares. The details of the instrumental variable regression are described in text. The R&D stock in Panel C is calculated using a 15% obsolescence rate. The number of observations in Panel A 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).

Table 2. 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).

Table 3. Heterogeneity of R&D Elasticity

	(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 4. Gross Returns to R&D

Obsolescence rate	1976-1991	1992-1999	2000-2007	2008-2018	Change
10%	.064	.043	.151	.165	.101
15%	.088	.058	.216	.235	.147
20%	.112	.074	.287	.311	.199
25%	.136	.090	.364	.394	.258
30%	.160	.106	.447	.483	.323
Addendum:					
Estimated obsolescence rate	.123	.080	.239	.315	.192
	(0.058)	(0.028)	(0.060)	(0.075)	

Note: To estimate the returns to R&D, output elasticities are first calculated by running the regression shown in Table 1, Panel C, 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. The obsolescence rates are calculated as described in the text from the regressions in Table 5. The standard errors of obsolescence rates are bootstrapped and shown in the parentheses. FSRDC Project Number 2735 (CBDRB-FY25-P2735-R12155).

Table 5. R&D Investment and Technological Rivalry

Period	1977-1991 (1)	1992-1999 (2)	2000-2007 (3)	2008-2018 (4)
Dependent variable: Log R&D				
Asinh(rival R&D$_{t-1}$)	-0.867*	-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

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. FSRDC Project Number 2735 (CBDRB-FY24-P2735-R11743, CBDRB-FY25-P2735-R12155).

Table 6. R&D Investment and Technological Rivalry, Additional regressions

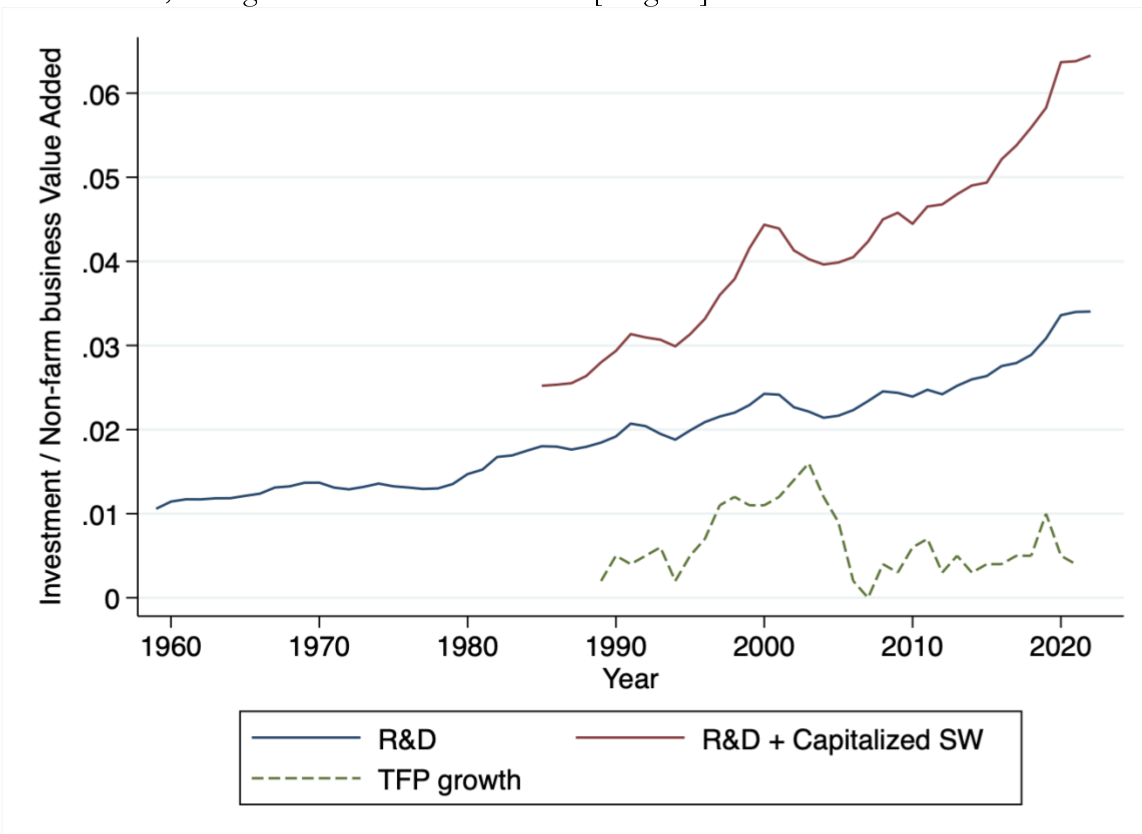
Period	1977-1991 (1)	1992-1999 (2)	2000-2007 (3)	2008-2018 (4)
A. Minimal controls; Dependent variable: Log R&D				
Asinh(rival $R\&D_{t-1}$)	-0.288*	-1.486***	-2.156***	-1.884***
	(0.147)	(0.178)	(0.196)	(0.183)
Adjusted R^2	0.338	0.461	0.339	0.207
Observations	20500	13000	17500	35000
B. Additional controls; 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).

Figures

Figure 1. Innovation investment relative to value-added

Source: BEA; TFP growth estimates from BLS [rndgro3]



References

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

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

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

Ando, Yoshiki, and James Bessen. 2025. "Endogenous Growth and Rising Obsolescence."

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): 1860–1918.

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

———. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35 (1): 128–52.

Cunningham, Cindy, Lucia Foster, Cheryl Grim, John Haltiwanger, Sabrina Wulff Pabilonia, Jay Stewart, and Zoltan Wolf. 2023. "Dispersion in Dispersion: Measuring Establishment-Level Differences in Productivity." *Review of Income and Wealth* 69 (4): 999–1032.

Doraszelski, Ulrich. 2003. "An R&D Race with Knowledge Accumulation." *Rand Journal of Economics*, 20–42.

Fernald, Kenneth D. S., Philipp C. Förster, Eric Claassen, and Linda H. M. van de Burgwal. 2024. "The Pharmaceutical Productivity Gap – Incremental Decline in R&D Efficiency despite Transient Improvements." *Drug Discovery Today* 29 (11): 104160. https://doi.org/10.1016/j.drudis.2024.104160.

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).

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.

———. 2009. "Productivity, R&D, and the Data Constraint." In *The Economic Impact of Knowledge*, 213–41. Routledge.

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*, 2:1033–82. Elsevier.

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

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.

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.

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

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

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

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.

Reinganum, Jennifer F. 1989. "The Timing of Innovation: Research, Development, and Diffusion." *Handbook of Industrial Organization* 1:849–908.

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

Appendix

Model

Elasticity regression with flow vs. stock

Under some general assumptions, estimates of R&D output elasticity based on the (lagged) current flow of R&D should equal estimates based on R&D capital stocks (see Hall, Mairesse, and Mohnen 2010, 1048). Assume that the R&D stock follows the perpetual inventory law of motion,

$$K_t = I_{t-1} + (1-d)K_{t-1},$$

where I_t is current R&D spending. Also assume that I_t grows at constant rate g—R&D grow rates tend to be highly persistent—so that $I_{t-1} = I_t/(1+g)$. Then

$$K_t = \sum_{\tau=1}^{\infty}(1-d)^{\tau-1}I_{t-\tau} = \sum_{\tau=1}^{\infty}\frac{(1-d)^{\tau-1}}{(1+g)^{\tau}}I_{t-1} = \frac{I_{t-1}}{g+d}$$

and equation (1) becomes

$$\ln R = \beta\ln K + \cdots = \beta\ln I_{t-1} - \beta\ln(g+d)\ \ldots$$

where the second term is absorbed into establishment or firm or industry fixed effects. The coefficient on $\ln I$ is the same as on $\ln K$. We find that our elasticity estimates are robust to different obsolescence rates and the use of current R&D.

Obsolescence and firm size

To consider how firm size affects R&D incentives, we rewrite the Bellman equation 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

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

Taking the derivative of (8),

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

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

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

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

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

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

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, $\overline{\log I_\iota} = \frac{1}{T}\sum_t \log I_{it}$. We can show that[24]

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

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

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 $var\overline{\left(\frac{I_\iota}{T_\iota}\right)}/var(S_{it})$ and find that it, too, is small but positive, reducing the net negative bias further. Relative to the estimates of $\hat{\beta}$ from Table 5, 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.

Table. Bias estimates

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

Profit function

The knowledge production function can be written

$$R = AX^\alpha K^\beta.$$

Maximizing with respect to the input factor given input price p_X,

$$\hat{X} = \frac{\alpha R}{p_X}.$$

Substituting $\hat{X}$ into the knowledge production function and rearranging,

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

Also

$$\Pi = \hat{R} - p_X\hat{X} = (1-\alpha)\hat{R}$$

from which it follows that

$$\Pi(K) = (1-\alpha)\hat{R}(K), \quad \Pi'(K) = \beta\frac{\hat{R}(K)}{K}. \qquad (A7)$$

We can obtain a similar expression from the Grossman/Helpman model. Here, let

$$n(1 - 1/\lambda) = K^\beta.$$

We have

$$R = nE, \quad \pi = n(1 - 1/\lambda)E$$

so that

$$\frac{\partial \pi}{\partial K} = \frac{\beta \pi}{K} = \beta \frac{R}{K}(1 - 1/\lambda). \tag{A8}$$

In the empirical implementation, we use version (A7) because we estimate β from the knowledge production function. Implementation using equation (A8) would simply sweep $(1 - 1/\lambda)$ into the fixed effects.

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. 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).

Table A3. 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 A4. 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 A5. R&D Investment with Instruments for Log Sales and for Rivals' R&D

Period	2000-2007 (1)	2008-2018 (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).