Rising obsolescence

Measuring obsolescence and its effect on R&D

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

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Note: This version is preliminary. Please do not share. Table 4 is currently under review for disclosure by the US Census.

Abstract:

Obsolescence is a central variable for understanding innovation. It affects firm decisions to invest in R&D and to adopt new technologies; it affects the calculation of R&D's contribution to productivity growth. Yet obsolescence rates are typically assumed to be constant over time and uniform across firms even in technologically dynamic sectors. This paper explores three measures of variable obsolescence based on patent citations (Ma 2025), patent renewals, and firm responses to rivals' R&D. All three measures are correlated, they all rose sharply since 2005, and they vary strongly with rivals' R&D. Obsolescence significantly affects firm R&D spending. And rising obsolescence reduces R&D's contribution to productivity growth, accounting for a significant share of the productivity slowdown after 2005.

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Introduction

Obsolescence is central to the economic analysis of innovation. In theory, the risk of obsolescence shortens the time horizons firms use to calculate the present value of profits they expect to receive from their investments in innovation. For this reason, obsolescence might be an important factor affecting firm decisions to invest in R&D, to adopt new technologies (thus diffusing innovations), and to expand production using innovative technologies (thus fostering reallocation of productive resources). Obsolescence is also essential to the construction of "knowledge stocks" (R&D stocks) used in productivity growth accounting.

Significantly, however, most of the analysis of innovation assumes static obsolescence—in the empirical literature, obsolescence rates are typically assumed to be constant for long periods of time, and they are usually assumed to be uniform for firms within the same industrial sectors.[1] Yet there are good reasons to expect that obsolescence might not be static in highly dynamic technology sectors: innovations using software or other new technologies may have shorter product life cycles; more intense technological rivalry could also raise obsolescence rates; and the enormous growth in private R&D in the US—tripling as a share of value added since the 1960s—provides a reason why obsolescence might be rising as in the Schumpeterian growth models (Aghion and Howitt 1992; Grossman and Helpman 1991). The assumption of constant and uniform obsolescence rates might not be appropriate in highly dynamic technology sectors.

This paper uses three different measures of obsolescence that change over time and differ across firms to explore variation in obsolescence rates. One measure was developed by Song Ma (2025) and two measures by us. These estimated obsolescence rates reject the assumption of static obsolescence. All three measures show large increases in obsolescence rates beginning after 2000. And we identify a major source of firm heterogeneity: firm obsolescence rates are strongly affected by rivals' innovative activity, which we measure in a variety of ways. Finally, we show that heterogeneous and variable obsolescence matters: firm obsolescence rates affect firm R&D investment, and rising obsolescence reduces the

[1] Caballero and Jaffe (1993), using a measure of technological obsolescence based on patent citations, find a long term rise in these obsolescence rates to 1990.

contribution of R&D to productivity growth. Rising obsolescence can account for a significant share of the slowdown in multifactor productivity growth in the US nonfarm business sector after 2005.

We begin using a recent measure of technological obsolescence based on patent citation data developed by Song Ma (2025), building on an approach introduced by Caballero and Jaffe (1993). Next, we use patent renewal data. Patents require periodic payment of maintenance fees to remain in force; firms avoid paying these fees for patents that are no longer sufficiently valuable, thus revealing information about the decline in value. Pakes and Schankerman (1984) first obtained econometric estimates using European renewal data. Bessen (2008) modified their approach to deal with US data.[2] Here we augment Bessen's method by using data on patent value from Kogan et al. (2017), improving the precision and reliability of our estimates. We also use patent term, the number of years a patent remains in force, for cross-sectional analysis. Finally, we estimate the economic impact of obsolescence by measuring the effect of obsolescence on firm R&D investment. We do this using an instrumental variable for obsolescence and these estimates allow us to infer economic obsolescence rates.

These approaches capture different concepts of obsolescence, and they apply to different samples. To understand the impact of obsolescence on R&D investment, on the adoption and diffusion of new technologies, and on firm growth and reallocation, we want a measure of economic obsolescence risk, that is, the expected risk to the stream of future profits. The citation obsolescence measure captures the decline in the tendency of future patents to cite patents in a firm's "technology base." Patent citations don't strictly correspond to technological importance (see Kuhn et al. 2020) and they may correspond even less to measures of the firm's profits from innovation, but they are nevertheless likely to be correlated with economic obsolescence as we see below. The patent renewal obsolescence measure reflects the depreciation of patents, not of the innovation per se. Patent values differ from innovation values because firms earn profits on their unpatented innovations and because patents have strategic value as a competitive tool even when the underlying innovation is defunct. The rise in the secondary market for patents reflects this

[2] In the United States, maintenance payments are due the 4th, 8th, and 12th years as opposed to annually, requiring log-likelihood estimation.

difference (Arora et al. 2022). Nevertheless, patent depreciation is likely correlated with economic obsolescence as we see below. Finally, the measure of obsolescence inferred from firm R&D investment is directly a measure of economic obsolescence. Note also that the samples differ. The patent-based measures both are limited to the important but highly select group of publicly listed firms that patent and perform R&D; the economic obsolescence measure is derived from all R&D-performing firms, and it can be applied more broadly as well.

The empirical literature on obsolescence rates begins with Pakes and Schankerman (1984) who estimated a 25 percent R&D depreciation rate using renewal data from several European countries during the 1930s. Since then, researchers have used a variety of methods including production function and market value analysis to obtain a range of estimates (see Mead and others 2007 for an overview and discussion of methods). Li and Hall (2020) review the prior estimates. Excluding outlier studies, the estimated R&D depreciation rates range from 11 to 41 percent.[3] The Bureau of Economic Analysis uses R&D depreciation rates ranging from 10 percent to 40 percent for different industries. Recent studies include Li and Hall (2020), who estimate rates for different industries for the period 1987-2007 from 6 percent to 73 percent, and Huang and Diewert (2011), who estimate rates for US manufacturing industries from 1953-2000 ranging from 1 percent to 29 percent.

But while these earlier R&D studies consider differences across industrial sectors, none evaluate differences within industries, and while a few do look at rough differences over time, none measure obsolescence at an annual frequency. Song Ma (2025) introduces a measure of technological obsolescence that does vary by firm and by year. Ma also found that his measure is related to slower firm growth and lower firm productivity. This paper contributes to the literature by providing two additional measures that differ by firm and year and by showing that obsolescence is strongly related to technological rivalry measured a variety of ways. It also contributes by showing that variable obsolescence is important for understanding firm incentives to invest in R&D and for measuring the contribution of R&D to multifactor productivity growth. Moreover, while the patent-based measures of obsolescence are limited to a select group of firms (publicly listed, patenting, and R&D-

[3] 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).

performing), the R&D based measure of obsolescence risk can be calculated for a much broader sample of firms, allowing more representative research.

We begin by discussing the patent-based measures of obsolescence. Then we show how they are related to technological rivalry and how both obsolescence and rivalry are related to firm R&D. We estimate the R&D regression using an instrumental variable based on rivals' R&D. Following Bloom et al. (2013) and Wilson (2009), we instrument rivals' R&D using state and Federal measures of the tax treatment of R&D. We further show that the reduced form of this regression equation allows us to invert the relationship between rivalry and obsolescence to obtain estimates of economic obsolescence. We show that this obsolescence measure has also grown substantially over the last two decades. Then, using the renewal measure of obsolescence, we calculate the contribution of R&D to multifactor productivity growth.

Data

The citation obsolescence data come from Ma (2025) who uses data from the US Patent and Trademark Office (USPTO) to generate obsolescence estimates for 212,000 patents from 1986 through 2022 for publicly listed firms. We link these obsolescence rates to Compustat firms using the DISCERN dynamic patent matching dataset (Arora, Belenzon, and Sheer 2021b).

The patent renewal data also comes from the USPTO which issues a weekly cumulative Patent Grant Maintenance Fee Events File. This lists events related to the maintenance of all US patents granted and subject to maintenance fees, including payments of fees and expiration for non-payment. We use data from the July 28, 2026, release which covers over 5 million patents. We also match these data to Compustat firms using the DISCERN matches. And, important for our renewal algorithm, we obtain the value of patent grants for publicly listed firms from Kogan et al. (2017).[4] These estimates of patent value are derived, under some assumptions, from the stock market reaction a few days

[4] The authors have extended these data through 2024. See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

around the date of the patent grant.[5] The matched data set contains just over 2 million patents with both maintenance and value information. The fee data come from the Federal Register and USPTO documents.

The R&D data come from two sources. For publicly listed firms, we use R&D expense reported in Compustat. For the broader sample of firms, we use the annual surveys of 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. These are 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 surveys collect data on up to 40,000 firms each year.

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.[6] 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 a variety of other information including firm revenue.

[5] Note that some researchers have raised questions about this method (Arora et al. 2026; Federle et al. 2026).

[6] 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.

Instrumental variable estimation

Below we regress firm obsolescence rates against rivals' R&D. To exclude confounding factors, we instrument rivals' R&D using state and Federal data on the tax cost of R&D. State and Federal tax laws provide R&D tax credits and other features that vary over time and state, affecting rivals' after-tax cost of R&D and hence rivals' R&D spending. Variations in rivals' R&D tax cost are plausibly independent of the focal firm's obsolescence risk, satisfying the exclusion restriction. The construction of the instrument was developed by Wilson (2009) and is described in the Appendix. R&D tax cost has been used to instrument rivals' R&D in the literature (Bloom et al. 2013; Lucking et al. 2019; Arora, Belenzon, and Sheer 2021a). The state-by-state tax data for each year were developed by Barth et al. (2023). For Compustat data (Tables 1 and 2) we assign the state based on the state of firm headquarters.

In Tables 2 and 3 we regress the log of firm R&D against $\ln(r+\delta)$ where δ is the obsolescence rate and r is the discount rate (assumed to be .05). Here, we hypothesize that $\ln(r+\delta)$ is a function of technological rivalry and we instrument this term using the sum of predicted rivals' R&D using state and Federal tax cost to predict each rivals' R&D. There is one significant difference with the above instrument, however, because the dependent variable is itself correlated with the focal firm's tax cost. To avoid violating the exclusion restriction, our prediction of $\ln(r+\delta)$ is based on the sum of predicted R&D for rivals' in the same industry but performed in *different states* from the focal firm.[7] Firm R&D is plausibly independent of the tax cost in other states except via the effect of these tax costs on the rivalry and the risk of obsolescence. Table 4 uses Census data that includes state-by-state breakouts of R&D expenditures for each firm. These data are available for most years; when state breakouts are not reported, we interpolate the share of expenditures made in each state under the assumption that firms do not frequently change the share of R&D done in each state.

A variety of other data are described as used in the text below.

[7] On average, less than 10 percent of rivals' R&D is performed in the same state as the focal firm [TBD]. And most R&D-performing firms have some industry rivals performing R&D in the same state. This avoids constructing the independent variable as a leave-one-out version of the dependent variable.

Patent obsolescence measures

Citation-based Obsolescence

Researchers have long hypothesized that patent citations reflect knowledge flows. Formally, patent applicants cite other patents to distinguish the claims in their patent application from prior art found in the cited patents. While some citations reflect a transfer of knowledge, perhaps most do not, reflecting patenting strategies, examiner preferences, and other factors. (Jaffe et al. 2000; Kuhn et al. 2020). Nevertheless, citations to patents decline over time, and this decline might provide a noisy indicator of a decline in the quality of the underlying technology and/or the economic value of the technology. Caballero and Jaffe (1993) use declining patent citations as a measure of technological obsolescence and Ma (2025) constructs his obsolescence measure based on this insight as follows. For a given base year, t_{base}, he defines the technological base as all the patents cited by the focal firm in that year or earlier (excluding the firm's self-citations). Then, for a set horizon of say 5 years, obsolescence is calculated as the percentage decline in the number of citations to this technological base from year t_{base} to year $t_{base} + 5$. We label this measure of citation obsolescence δ_c.

Using a 5-year horizon, Ma estimates an average annual obsolescence rate of 3.9 percent. This is much lower than the estimates of R&D depreciation in the literature, but it is measuring something very different. Nevertheless, we might expect this measure might be related to economic obsolescence—as the quality of a firm's technology declines, the profit-making potential of that technology might well also decline. Ma reports that his measure is negatively correlated with firm productivity and firm growth. Below we test the association between this measure and firm R&D investment, finding a negative relationship.

And this measure has changed over time. Figure 1 shows the mean annualized rate of obsolescence using a five-year horizon for all of the firms in the sample. The year displayed is the base year. There has been a sharp increase after 2005 or so.

Renewal-based Obsolescence Estimates

At most national patent offices, payment of periodic maintenance fees is required to keep a patent in force. Since Pakes and Schankerman (1984), economists have used data on

fee payments to infer patent value and depreciation rates. The idea is that patents lose value over time thanks to obsolescence. A patent that is worth $10 million when granted depreciates in value so that after, say, 12 years, a firm might not be willing to pay a fee of $3000 to keep the patent in force. Under some assumptions, data on many such events can be used to infer obsolescence rates.

Beginning in 1982, the US patent office began charging maintenance fees in the 4th, 8th, and 12th years after the patent grant.[8] These fees keep the patent in force until the next fee is due or until the patent reaches its maximum term.[9] A firm's decision to pay this fee and renew the patent reveals information about the depreciation rate. Let the depreciation rate for a patent be δ and let the initial stream of profits from the patent be $\pi(0)$. We assume that the depreciation rate is constant over the life of the patent. Then the profit stream at year *t* will be $\pi(t) = \pi(0)e^{-\delta t}$. Suppose that at year *t* a fee of f_t is due and that payments will keep the patent in force another *T* years. Then the firm will decline to pay this fee if the expected present value of keeping it in force the additional *T* years is less than the fee, f_t. That is, if the patent has been renewed up to year *t,* it will not be renewed further if

$$\int_t^{t+T} \pi(\tau)e^{-(r+\delta)\tau}\, d\tau = \pi(0)e^{-\delta t}\frac{1-e^{-(\delta+r)T}}{\delta+r} < f_t \qquad (1)$$

where *r* is the discount rate.

Given this equation, if we observe non-payment of the fee in year *t*, we could determine the depreciation rate (within *T* years) if we knew the profit flow, $\pi(0)$. Beginning with Pakes and Schankerman, researchers have done this by assuming a distribution function (Pareto or lognormal) for $\pi(0)$ and then fitting the data for multiple years to estimate the parameters of that distribution.[10]

Here, we improve on this approach by using an additional piece of data: the estimated value of the patent at grant. Kogan et al. (2017) estimate these values—the "KPSS" values—using the stock market reaction around the patent issue date. While these

[8] The fees are due at 3.5, 7.5, and 11.5 years, respectively, although a system of late fees permit later payments. For simplicity, we assume the payments are made at 4, 8, and 12 years.

[9] Prior to 1995 this term was 17 years from the grant date. Since then, the patent term is 20 years from the patent application filing date. There are some exceptions and extensions, but we ignore those.

[10] They did this for several European patent offices where the fees are due annually. Bessen (2008) developed a method for US data where the fee intervals are longer.

estimates are subject to error noise, the additional information should improve the precision and reliability of our estimates, permitting us to obtain annual estimates of patent depreciation rates without difficulties in maximum likelihood estimation. We assume that the patent value, V, equals the expected present value of the profit stream from the patent from the grant year to through the expected life of the patent, T_F,

$$V = \int_0^{T_F} \pi(0) e^{-(r+\delta)\tau}\, d\tau = \pi(0) \frac{1 - e^{-(\delta+r)T_F}}{\delta + r}. \quad (2)$$

Further, we assume that the true patent value, V, is related to the KPSS estimate of patent value, V^{KPSS}, by a lognormal error, $\ln V = \ln V^{KPSS} + \epsilon,\ \epsilon \sim N(0, \sigma^2)$.[11] Then, using (1) and (2) and taking logs, a firm will not renew patent *i* at time *t* if (adding subscript *i*),

$$\epsilon_i < \ln f_t + \delta_i t - \ln V_i^{KPSS} + \ln z\,, \quad z \equiv \frac{1 - e^{-(\delta+r)T_F}}{1 - e^{-(\delta+r)T}}. \quad (3)$$

Using the normal cumulative distribution function, $\Phi(\cdot)$, the unconditional probability that patent *i* will not renew at time *t* is

$$P_t\left(\delta_i, V_i^{KPSS}\right) = \Phi\left(\frac{\ln f_t - \ln V_i^{KPSS} + t\delta_i - \ln z}{\sigma}\right), \quad t = 4,8,12. \quad (4)$$

We use these probabilities in two sorts of analysis. First, for each year for each firm we retrospectively measure the mean life of that firm's patents, that is, the mean number of years its patents were kept in force. To compare mean patent lives across firms, we note that, using equation (4), the a priori expected life, D, of patent *i* granted at *t*=0, is

$$\mathbb{E}[D] \equiv 4P_4 + 8(P_8 - P_4) + 12(P_{12} - P_8) + T_F(1 - P_{12}). \quad (5)$$

This tells us that the expected patent life for a firm's patents for a given year is a function of the obsolescence rate and values of the firm's patents. It is straightforward to show that expected patent life increases with patent value and decreases with obsolescence, $\frac{\partial \mathbb{E}[D]}{\partial V^{KPSS}} > 0$ and $\frac{\partial \mathbb{E}[D]}{\partial \delta} < 0$. This means that controlling for each firm's mean patent value, for a given

[11] This is reasonably consistent with Kogan et al. (2017, 678) where the error is a normally distributed variable times the firm market capitalization. Market capitalizations are distributed lognormally. Several papers have explored the distribution of invention value, finding it is consistent with a lognormal distribution which fits the data better than Pareto or Weibull distributions (Harhoff et al. 2003; Lanjouw 1998; Schankerman and Pakes 1986; Schankerman 1998). Other papers have tested whether depreciation rates are constant (Pakes 1986; Lanjouw 1998); while there is some evidence of initially increasing patent value, that process appears complete by the fourth year after patent grant (our first data year) and follows a steady decline after that.

grant year differences in mean patent life reflect differences in firm obsolescence rates. Controlling patent values, shorter patent lives imply higher obsolescence rates, allowing us to conduct a cross-sectional analysis of factors that affect obsolescence rates.

Second, assigning all patents in a given grant year have the same average depreciation rate (deviations fall into the error term), we can construct a log-likelihood function,

$$\ln L = \sum_i \ln P_4 \, \mathbb{I}[t = 4] + \ln(P_8 - P_4) \, \mathbb{I}[t = 8] + \ln(1 - P_8) \, \mathbb{I}[t > 8] \qquad (6)$$

where *t* designates the year that the patent lapsed. We maximize the likelihood function to estimate the average depreciation rate for each grant year.[12] Note that this equation could be written to include the 12th year renewal; by using renewal data only through the first 8 years, we are able to extend the analysis to 2018 (for data that go to 2026). We label this measure of obsolescence as δ_p. Running the 12-year estimation, yields a similar pattern of rising rates over a truncated period, although depreciation levels are higher.[13]

Here the obsolescence rates are more like the R&D depreciation rates in the literature, ranging from about 20 percent to 40 percent. This series also shows a dramatic rise in obsolescence rates beginning in the mid-2000s as seen in the solid line in Figure 2. The values are listed in Appendix Table A3. Because we want to focus on economic obsolescence, we suppress the results for the late 1980s (although they are similar to the early 1990s); the secondary market for patents expanded dramatically during the 1980s (Arora, Belenzon, and Suh 2021), so the patent depreciation rates might have diverged significantly from economic obsolescence rates then.

One concern with these estimates is that the KPSS patent values have been subject to some criticism (see Wang 2023; Arora et al. 2026; Federle et al. 2026). One problem cited concerns how KPSS infer patent values from the stock market reactions immediately after patent grants. KPSS assume that prior to the patent grant, the stock market has full knowledge of the value of the patented invention *except* for the probability that the patent

[12] This analysis assumes that patents in a given grant year face the same depreciation rate for 8 years. This might seem in conflict with our finding of rising depreciation rates, but it is a reasonable first order approximation. Monte Carlo tests using depreciation rates that increase .5 or 1 percent per year yield results that are close to the mean depreciation rate. We estimate T_F from the firm's actual mean patent life, assuming managers have perfect foresight. The obsolescence estimates are not sensitive to this choice.

[13] This could be because the KPSS values may be biased for high value patents (Arora et al. 2026).

will be granted. Then the stock market reaction only represents the value of this additional information. They derive the total patent value by dividing the increase in stock market value by the average probability that a patent application will be granted. Since the average probability that a patent will be granted is 56 percent, they divide the stock market increase by (1 - .56). Wang (2023) argues that this probability likely changes as the lag since the patent application was filed grows. He evaluates this effect, concluding that the KPSS patent values are overstated by 50 percent. Federle et al. (2026) look at problems that arise when firms are granted multiple patents on the same day. In these cases, firms gain market value on average, but that value has to be allocated across multiple patents. Federle et al. (FHK) use this by predicting the relative values of the patents sharing a common grant date using additional data on patent characteristics that are available prior to the grant; for instance, they regress patent values from the PATVAL survey against patent characteristics to determine relative values. They also consider how patent characteristics affect the "noise" in the stock market regression. To test the robustness of our obsolescence estimates, we run the calculation using patent values from Wang and from FHK. Results using these assumptions are shown in Appendix Table A3 and in Figure A1. While the assumptions do affect the depreciation estimates, the effects are not large and the rising trend in obsolescence rates is unaffected.

Firm Heterogeneity

Table 1 shows mean differences in these measures between groups of firms based on selected characteristics. The first column reports differences in firm mean citation obsolescence; the second column reports differences in mean firm patent life. Higher citation obsolescence roughly corresponds to shorter patent life, as we might expect. Firm that are younger in the sense of more recently going public (IPO in the last 5 years) have longer patent lives on average (the measure of obsolescence with a 5-year horizon is not meaningful for this group). Firms in the manufacturing sector have higher obsolescence and shorter patent lives on average. Firms that are in technological industries[14] or that have above median R&D to sales ratios have lower obsolescence and longer patent lives on average. Firms with patents that have high KPSS values (over $500 million) on average do

[14] Firm in NAICS 3254, 3341, 3343, 3345, 5112, 5173, 5182, 5415, or 5417.

not have significantly different citation obsolescence and have slightly shorter patent lives. One source of firm differences in obsolescence might be differences in technological rivalry.

Obsolescence and Rivalry

Next, we turn to the hypothesis that technological rivals increase obsolescence risk. In Schumpeterian growth models, obsolescence arises from the innovative activity of rivals. More generally, other firms, who might or might not be close product market rivals, develop innovations that can replace focal firm products or, in a differentiated market, can reduce the profit on focal firm innovations. But is there evidence that obsolescence does rise with technological rivalry? In Table 2, we test this hypothesis by regressing obsolescence measures against a variety of measures of technological rivalry. If rivals' technological activity reduces focal firm profits (economic obsolescence), this might show up as a higher citation obsolescence rate for the firm or shorter patent lives; that is, patentees might be less likely to cite a patent that is no longer economically valuable and firms may be less likely to renew such a patent.

Table 2A, using citation-based obsolescence as the dependent variable, shows the relationship for several measures of technological rivalry:

1. The first column uses the inverse hyperbolic sine of the sum of real R&D by other firms in the same 6-digit NAICS industry. We use the inverse hyperbolic sign rather than the log because the values are small for some industries.
2. The second column uses the inverse hyperbolic sine of the sum of the KPSS values of patents granted to other firms in the same 6-digit NAICS industry. This is a measure of R&D output rather than input (see Kogan et al. 2017; 2025).
3. These first two measures treat rivals as firms in the same detailed industry, but this might not reflect the best measure of rivalry. We might want to use a distance measure to capture R&D by product market rivals. The third column uses the sum of other firms' R&D weighted by the Hoberg-Phillips proximity weights (2016). These weights identify product market rivals by comparing text descriptions of firm business lines.
4. Alternatively, we might want to measure R&D from firms working in similar technology areas. Since Jaffe (1986), researchers have used patent-class similarity to measure technological proximity (see also Bloom et al. 2013; Arora, Belenzon, and

Sheer 2021a). We use the technology proximity of other firms calculated by Arora, Belenzon, and Sheer as the Mahalanobis similarity of vectors representing the shares of patents across 4-digit international patent classes (IPC) for each pair of firms. The fourth column uses the sum of other firms' R&D weighted by this Mahalanobis distance.

These rivalry measures are correlated with each other, and they are all correlated with the obsolescence rate. The independent variables shown are standardized by dividing each by its standard deviation. All these regressions use firm and year fixed effects, but it is still possible that some third factor might be correlated both with obsolescence and the rivalry measures. To identify the effect of rivals' innovative activity, we use an instrumental variable. The instrument is based on state and Federal tax costs of R&D. Variations in tax cost across states and over time affect rivals' cost of R&D and are thus correlated with rivals' R&D. However, these tax costs are unlikely to be correlated with the focal firm obsolescence rates except through their effect on rivals' R&D. In the Appendix, we describe the instrument in greater detail. Following Bloom et al. (2013), we calculate the predicted R&D for each rival firm and total these predicted values. Column 5 shows the regression with the inverse hyperbolic sine of the sum of predicted R&D by other firms in the same 6-digit NAICS industry. We use this measure of technological rivalry because it can be calculated without patent data; this will become useful below. This instrumented measure is correlated with the firm obsolescence rates, suggesting that the link between technological rivalry and obsolescence is plausibly causal.

We explore the relationship between technological rivalry and firm renewal behavior in Table 2B. From equations (4) and (5), expected firm patent life is an increasing function of patent value and a decreasing function of the obsolescence rate. Table 2B regresses the mean life of patents granted to each firm in a year (retrospectively determined) against the same measures of technological rivalry as in Table 2A. Controlling for patent value, the negative effect of technological rivalry on mean patent life should correspond to a positive effect on the obsolescence rate.

The rivalry measures are highly correlated with each other, and they are all correlated with both obsolescence measures; greater technological rivalry has a significant positive association with citation obsolescence and a negative association with patent term,

corresponding to higher obsolescence. The last column of Table 2B shows that patent life is negatively correlated with the citation measure of obsolescence. Although renewal obsolescence and citation obsolescence represent different concepts, they correspond with each other. Technologically proximate rivalry appears particularly influential. Indeed, a standard deviation increase in technologically proximate R&D is associated with over a two year reduction in the firm's mean patent life. Moreover, the instrumental variable analysis suggests that these relationships are plausibly causal, that is, greater rivalry likely causes higher obsolescence. This analysis supports the hypothesis that greater technological rivalry heightens obsolescence rates. And, as we see next, this relationship provides a foundation for estimating economic obsolescence.

Economic Obsolescence

Obsolescence and firm R&D

These patent-based measures show evidence of strongly rising obsolescence rates and a strong relationship between technological rivalry and obsolescence. But the economic significance of these findings depends on the relationship between obsolescence and firm investment in innovation. In theory, the risk of obsolescence should affect firm investments in R&D, in new technology adoption, and in the expansion of production based on new technologies. A common intuition holds that greater obsolescence decreases the effective time horizon over which a firm can profit from an innovation and this leads the firm to invest less.

A simple model illustrates this intuition for the case of R&D investment. Consider a firm that wants to invest I in R&D at time 0 to develop an innovation that is expected to generate a stream of profits, $\pi_t, t = 1,2, \ldots$ Let productivity be a diminishing function of I and a random productivity shock, $A_t = \overline{A} I^{\beta} + \nu, 0 < \beta < 1$, where the output elasticity β is less than one to capture diminishing returns to R&D. With labor L_t as the input, output is $Q_t = A_t L_t = \overline{A} I^{\beta} L_t$. Assuming static optimization of labor at a constant wage, w, and a markup, μ, it is straightforward to show that revenue is then $\overline{R}_t = Q_t^{1/\mu}$ and $\pi_t = \overline{R}_t \left(\frac{\mu-1}{\mu}\right)$. The firm will then seek to maximize the expected present value of the innovation,

$$V = \max_{I} \left[\sum_{\tau=0}^{\infty} B^{\tau} \mathbb{E}[\pi_t] - p_I I \right], \quad B \equiv \frac{1-\delta_e}{1+r}. \tag{7}$$

where the discount rate is r and the expected economic obsolescence rate δ_e, which we assume to be constant. Economic obsolescence, δ_e, represents a decrease in firm profits either from replacement of the focal firm's innovation or a reduction in its profits from competition in a differentiated market. Taking the first order maximizing condition, rearranging and taking logs, we get a log R&D demand equation,

$$\ln I = \ln \overline{R} - \ln(r + \delta_e) + \ln \frac{\beta}{\mu} + FE \tag{8}$$

sweeping constant terms into fixed effects. Greater economic obsolescence corresponds to lower R&D. Similar models can be shown addressing the effect of obsolescence on technology adoption and on the expansion of production using new technology (see for instance Ando et al. 2025a).

Patent-based obsolescence and firm R&D

To explore equation (8), we first use renewal-based obsolescence as a proxy for economic obsolescence. Specifically, we hypothesize that the effective economic life of an innovation is highly correlated with the useful life of related patents so patent life can serve as a proxy. We expect that firms will want to keep patents in force as long as the associated innovation generates significant profits. This correspondence is not exact; innovations may generate profits after the patents have expired. But the proxy assumption may hold frequently enough. In equation (7), δ_e is constant so the expected profits are subject to exponential depreciation with a mean economic life of $1/\delta_e$. Assuming that this economic life is roughly equal to the mean patent life, D, the patent-life proxy for economic obsolescence is $\delta_p = 1/D$.[15]

Table 3 tests equation (8) using this proxy variable. As a baseline, columns 1 and 2 show the relationship between log R&D for the firm and citation obsolescence and $1/D$, respectively. The regression includes fixed effects of detailed industries-by-year. Both obsolescence measures are negatively correlated with firm R&D. Column 3 uses the actual

[15] Expected patent life changes from year to year because of changing patent values and fees (equations 4 and 5). For this reason, year fixed effects are important here.

specification of equation (8), using .05 as the discount rate, again finding a negative correlation.[16]

These correlations are interesting, but it would be helpful to isolate the effect of obsolescence on R&D from third factors that might affect both R&D and obsolescence. To do this, as a first pass, we do an instrumental variable estimation. Above, we showed that obsolescence rates are strongly related to rivals' R&D. Table 2B, column 5 relates the patent-term to predicted rival firm R&D, where the prediction is based on R&D tax cost. We use this same instrumental variable to predict obsolescence in $\ln(r+\delta)$ in column 4 (we bootstrap the two-step regression, and we exclude R&D performed in the same state as the focal firm). The coefficient of $\ln(r+\delta)$ is again highly significant and similar to the coefficient obtained via OLS in column 3. This regression does not consider some important confounding influences such as knowledge spillovers; we address these with the more extensive Census data below.

R&D-based obsolescence

But the reduced form version of this regression provides further insights. In column 5 we estimate the reduced form as

$$\ln I = \gamma_R \ln R + \gamma_z \operatorname{asinh} \hat{z} + FE + \epsilon \tag{9}$$

where $\hat{z}$ is the sum of rivals' predicted R&D as above, using the prediction based on R&D tax cost and excluding rival R&D performed in the same state as the focal firm. The coefficient is, not surprisingly, highly significant.

It is helpful to interpret this regression using a structural assumption. Let

$$\ln(r+\delta) = \ln r - \gamma_z \operatorname{asinh} \hat{z}\,. \tag{10}$$

With this specification, $\ln(r+\delta)$ becomes larger as rivals' R&D increases (recall that $\gamma_z < 0$) and $\ln(r+\delta) \to \ln r$ as $\hat{z} \to 0$, both as we expect. Then, we can invert equation (10) to obtain the obsolescence rate at the sample mean,

$$\hat{\delta}_r = r\left(e^{-\hat{\gamma}_z \overline{\operatorname{asinh} z}} - 1\right). \tag{11}$$

[16] We cannot use the citation-based obsolescence measure in this way because about one third of the observations have negative values for this variable which does not make good sense in this context.

For column 5 (shown in the bottom row), assuming a 5 percent discount rate, this implies a mean obsolescence rate of 28 percent. Despite the small sample, this estimate is similar to other estimates in the literature.

Note that this is an *economic* obsolescence rate. Patents are not involved in the estimation, and the value derives from the interaction of rivals' R&D and own-firm R&D. Importantly, Table A4 in the Appendix shows that this measure of obsolescence is correlated with the citation- and renewal-based measures, δ_c and δ_p. That means this obsolescence rate can be calculated for firms that do not patent and obsolescence risk can be calculated for firms that do not do their own R&D, but who may license an innovative technology. We proceed to estimate this R&D-based obsolescence measure for the US nonfarm business sector and for the US manufacturing sector in Table 4.

However, several econometric concerns affect identification in these regressions. First, rivals' R&D doesn't only affect the focal firm's obsolescence risk; it also affects the firm via knowledge spillovers. That is, knowledge from rivals could enhance the productivity of own-firm R&D, raising the output elasticity β that enters equation (8) and possibly biasing the estimates of γ_z.[17] In the Appendix, we estimate this spillover effect using variables developed in a related paper (Ando et al. 2025b). That paper estimates β, the output elasticity of R&D by regressing firm productivity on the firm's R&D stock. Here we add an additional term to that regression, the R&D stock times the inverse hyperbolic sine of rivals' R&D. This term captures the extent to which spillovers from rivals increases the output elasticity and hence increases the level of R&D as in equation (8). The spillover effect is statistically significant and positive; consistent with the literature, this means that rivals' R&D complements own-firm R&D (Bloom et al. 2013; W. M. Cohen and Levinthal 1989, 1990). However, the effect is not large—it increases R&D modestly (see Appendix). We adjust firm R&D to back out the contribution of spillovers, and we then use this adjusted R&D measure in the regressions. The Appendix also shows the regressions without this adjustment; the estimated obsolescence rates are slightly higher with the adjustment.

[17] Spillovers might alternatively directly affect firm output if knowledge improved productivity without any additional own-firm R&D. In this case the effect of spillovers would be absorbed in the revenue term of equation (9) and not affect estimates of γ_z.

A second concern arises from confounding influences such as common productivity shocks or changes to product market competition that might affect both focal firm R&D and rivals' R&D. These common shocks would create a positive bias tending to understate our estimates of γ_z. As above, we use an instrumental variable based on variations in state and Federal tax law that affect the tax cost of rivals' R&D, using this to predict rivals' R&D. For each firm year, we sum rivals' predicted R&D, excluding R&D conducted in the same state as the focal firm's main R&D lab. This measure is plausibly unaffected by common technology shocks or market competition conditions, but it is correlated with firm obsolescence rates as above.

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

[Note: The data for Table 4 have not been disclosed by the US Census. Instead, we show similar regressions that have been disclosed.]

Table 4 shows regressions of equation (9) 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 adjusted for spillovers, and the regressions include detailed industry and year fixed effects. 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.[18]

We also add an interaction term between rivals' R&D (predicted) and log firm revenue, $\gamma_x \operatorname{asinh} \hat{z} \cdot \ln R$. We do this to capture 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

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

introduces a superior product. Then, the obsolescence rate will be lower. With this additional term, the measure of obsolescence at the sample mean is[19]

$$\hat{\delta}_r = r\left(e^{-\hat{\gamma}_z \overline{\text{asinh } z} - \hat{\gamma}_x \overline{\ln R \cdot \text{asinh } z}} - 1\right). \tag{12}$$

Panel A shows estimates for the nonfarm business sector; Panel B shows estimates just for the manufacturing sector. The coefficients on predicted rivals' R&D are highly significant, negative, and economically substantial. Consistent with Table 3, obsolescence appears to have a substantial negative effect on firm R&D.

The bottom row of each panel shows the obsolescence rate calculated at the sample mean using equation (12). The standard errors are bootstrapped. The obsolescence rates for the nonfarm business sector are also shown in Figure 2 along with estimates derived from patent renewal data. The obsolescence rates calculated using R&D data are broadly similar to the annual data calculated using the renewal method, exhibiting the same sharp rise after around 2005. This suggests that while these two measures are conceptually different, for many practical applications the renewal measure may provide a useful proxy of economic obsolescence.

Rising Obsolescence and TFP Growth

Rising obsolescence also affects the contribution of R&D to productivity growth. In the productivity accounting literature (Sveikauskas 1986; U.S. Bureau of Labor Statistics 1989, 2026), the contribution of R&D to output growth and to multifactor productivity growth occurs via an R&D stock, K, calculated using the perpetual inventory method,

$$K_t = (1-\delta)K_{t-1} + I_{t-1} \tag{13}$$

where δ is the depreciation or obsolescence rate and I is real R&D investment. Output is assumed to be a function of this R&D stock in addition to other inputs so that multifactor productivity growth is

$$\frac{\dot{A}}{A} = \frac{\dot{C}}{C} + \alpha_t \frac{\dot{K}}{K} \tag{14}$$

[19] This interaction term is highly significant in the fourth period. Table A?? in the Appendix shows the regression without this interaction term. The obsolescence estimates are somewhat lower, but still show a sharp rise.

where A is multifactor productivity, C captures other sources of productivity, and α_t is the factor share of R&D. The second term represents the direct contribution of R&D to productivity growth; it does not include the contribution of spillovers. In equilibrium, the factor share of R&D is the Jorgensonian user cost of the R&D stock divided by output (value added, V, in this case):

$$\alpha_t = \frac{p_{It}(r_t + \delta_t)K_t}{V_t} \tag{15}$$

where p_I is the deflated price of R&D and r is the real interest rate.[20]

From these equations, rising obsolescence affects the productivity growth calculation in two ways: it slows the growth of the R&D stock, and it raises the user cost of R&D. We can gauge the significance of these effects by constructing an R&D capital stock using our annual estimates of the renewal obsolescence rate, δ_p. We apply these rates to data on real US private investment in R&D for the nonfarm business sector. Figure 3A shows the growth of the R&D stock for the US nonfarm business sector; Figure 3B shows the contribution of private R&D in this sector using equation (15) assuming a real interest rate (including risk premium) of 10 percent; for reference, a dashed line shows the BLS multifactor productivity growth rate. In the face of rising obsolescence, the R&D stock more or less stopped growing for a decade after 2005 even though R&D investment grew at about 4 percent per year during this period. And although the R&D share of output rose, Figure 3B shows that the contribution of R&D to productivity growth also fell after 2005. This decline of more than a quarter of a percentage point corresponds to roughly half of the decline in TFP from before 2005 to after 2010. Thus, rising obsolescence can account for a significant share of the productivity growth slowdown after 2005. Of course, other factors have influenced the productivity slowdown, including possibly an obsolescence-related decline in R&D spillovers. But this exercise shows that variable obsolescence may be an important factor to include in productivity analysis.

[20] In some treatments, the private marginal return on R&D is further assumed to be equal to this marginal cost; the marginal return is assumed to take a fixed value derived from empirical studies (e.g., .30). Here we use the cost share approach because the depreciation rate is changing and because there is evidence that marginal returns to R&D are also changing (Ando et al. 2025b).

Conclusion

Our analysis rejects the assumption that obsolescence rates are constant over time and uniform across firms. While obsolescence can be measured in several ways, all three measures we use show a sharp rise in mean obsolescence rates over the last two decades. And we find that firm obsolescence rates are strongly related to R&D rivalry measured in a variety of ways including rivals' R&D expenditures in the same primary industry, weighted by product market proximity (Hoberg and Phillips), and weighted by technological proximity (Mahalanobis distance of patent technology classes). Among other factors, rivalry generates significant firm heterogeneity in obsolescence rates.

And variable obsolescence appears to be important for economic analysis of innovation. We find that obsolescence risk exerts a strong negative influence on R&D investment, both in Compustat firms and in the broad Census sample. And we find that rising obsolescence considerably diminishes the contribution of R&D to productivity growth, accounting for a significant portion of the slowdown in multifactor productivity growth for the US nonfarm business sector.

While Creative Destruction may generate productivity growth on net, it clearly has a downside as well, and policies may be able to temper the negative effects.

More generally, our findings suggest that rising and heterogeneous obsolescence rates might have important implications for understanding R&D investment, the adoption and diffusion of new technologies, firm growth, and the reallocation of production to innovative technologies. The new measures of obsolescence may be helpful for this research agenda. In two related papers, we use R&D-based measures to explore the impact of R&D rivalry on how R&D affects firm productivity growth and on firm growth (Ando et al. 2025b, 2025a).

And our findings also raise the question of why obsolescence rates have risen. One factor may be rising R&D rivalry as firm investment in R&D has deepened perhaps because R&D has become more effective (Ando et al. 2025b). Another factor might be the shift of R&D away from research and towards development, suggesting a switch to shorter-lived innovations and perhaps a smaller "inventive step" (Arora et al. 2020). Another factor might be the changing nature of R&D—by 2021, nearly half of R&D was software development

which might generate shorter-lived products. Understanding these phenomena might be important for understanding and improving the connection between innovation and productivity growth.

References

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

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

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

Arora, Ashish, Sharon Belenzon, Ella Ferracutti, and Jay Prakash Nagar. 2026. "Revisiting Stock Market Signals as a Lens for Patent Valuation." *Organization Science*, ahead of print. https://doi.org/10.1287/orsc.2025.20570.

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.

Arora, Ashish, Sharon Belenzon, and Lia Sheer. 2021a. "Knowledge Spillovers and Corporate Investment in Scientific Research." *American Economic Review* 111 (3): 871–98.

Arora, Ashish, Sharon Belenzon, and Lia Sheer. 2021b. "Matching Patents to Compustat Firms, 1980–2015: Dynamic Reassignment, Name Changes, and Ownership Structures." *Research Policy* 50 (5): 104217. https://doi.org/10.1016/j.respol.2021.104217.

Arora, Ashish, Sharon Belenzon, and Jungkyu Suh. 2021. "Science and the Market for Technology." No. 3799825. NBER Working Paper 28534. Preprint, Rochester, NY, March 1. https://papers.ssrn.com/abstract=3799825.

Arora, Ashish, Sharon Belenzon, and Jungkyu Suh. 2022. "Science and the Market for Technology." *Management Science* 68 (10): 7176–201.

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*.

Barth, Erling, James C. Davis, Richard B. Freeman, and Kristina McElheran. 2023. "Twisting the Demand Curve: Digitalization and the Older Workforce." *Journal of Econometrics* 233 (2): 443–67.

Bessen, James. 2008. "The Value of US Patents by Owner and Patent Characteristics." *Research Policy* 37 (5): 932–45.

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

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

Caballero, Ricardo J., and Adam B. Jaffe. 1993. "How High Are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth." *NBER Macroeconomics Annual* 8: 15–74.

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.

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

Federle, Jonathan, Dietmar Harhoff, and Ann-Christin Kreyer. 2026. "Value Estimates for Us Patent Grants." *Max Planck Institute for Innovation & Competition Research Paper*, nos. 26–08.

Green, Brice, Leonid Kogan, Dimitris Papanikolaou, and Lawrence Schmidt. 2025. "Winners and Losers: Competition, Creative Destruction, and Labor Income Risk." *Creative Destruction, and Labor Income Risk (December 16, 2025)*.

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

Hoberg, Gerard, and Gordon Phillips. 2016. "Text-Based Network Industries and Endogenous Product Differentiation." *Journal of Political Economy* 124 (5): 1423–65.

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.

Jaffe, Adam B. 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms, Patents, Profits and Market Value." *American Economic Review* 76: 984–1001.

Jaffe, Adam B., Manuel Trajtenberg, and Michael S. Fogarty. 2000. "Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors." *American Economic Review* 90 (2): 215–18.

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.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *The Quarterly Journal of Economics* 132 (2): 665–712.

Kuhn, Jeffrey, Kenneth Younge, and Alan Marco. 2020. "Patent Citations Reexamined." *The RAND Journal of Economics* 51 (1): 109–32. https://doi.org/10.1111/1756-2171.12307.

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.

Ma, Song. 2025. "Technological Obsolescence." *The Review of Financial Studies*, hhaf059.

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

Pakes, Ariel, and Mark Schankerman. 1984. "The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources." In *R&D, Patents, and Productivity*. National Bureau of Economic Research, Inc.

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

Sveikauskas, Leo. 1986. "The Contribution of R& (and) D to Productivity Growth." *Monthly Lab. Rev.* 109: 16.

U.S. Bureau of Labor Statistics. 1989. *The Impact of Research and Development on Productivity Growth*. Bulletin No. 2331. U.S. Government Printing Office. https://www.bls.gov/productivity/articles-and-research/the-impact-of-rd-on-productivity-growth.pdf.

U.S. Bureau of Labor Statistics. 2026. "Contribution of Research and Development (R&D) to Private Nonfarm Business Sector Total Factor Productivity." Bureau of Labor Statistics. https://www.bls.gov/productivity/highlights/research-and-development-contribution-to-total-factor-productivity.htm.

Wang, Wenjun. 2023. *Valuation of Patents Using Stock Market Responses*. University of California, Berkeley.

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.

Tables

Table 1. Difference in obsolescence by firm characteristics

	Citation Obsolescence	Patent Life
Newly public (IPO<5 years)	--	0.367 (0.048) ***
Manufacturing	0.039 (0.007) ***	-0.293 (0.048) ***
Technology intensive industry	-0.105 (0.005) ***	0.200 (0.037) ***
Above median R&D/sales	-0.087 (0.005) ***	0.545 (0.035) ***
Mean patent value > $500m	0.002 (0.006)	-0.186 (0.039) ***

Note: significance test is a t-test of the difference.

Table 2A. Endogeneity of Citation Obsolescence

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Firm citation obsolescence, δ_c				
asinh(other R&D)	0.080***				
	(0.015)				
asinh(other patent value)		0.022**			
		(0.011)			
rivals' R&D (Hoberg)			0.023***		
			(0.005)		
Ln Mahalanobis R&D				0.184***	
				(0.017)	
asinh(other R&D) IV					0.045***
					(0.014)
N	28611	15750	47433	39255	19748
R^2	0.459	0.467	0.365	0.328	0.435
rivals	NAICS 6-digit	NAICS 6-digit	Market distance	Tech distance	NAICS 6-digit

Note: Robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions have firm and year fixed effects, and all independent variables are standardized (divided by their standard deviations). Regressions using NAICS industries exclude industries with less than $1 billion ($2017) in total industry R&D.

Table 2B. Endogeneity of Patent Term

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Mean firm patent term					
Log patent value	0.209***	0.204***	0.279***	0.259***	0.195***	0.204***
	(0.029)	(0.030)	(0.025)	(0.023)	(0.030)	(0.031)
asinh(other R&D)	-0.752***					
	(0.114)					
asinh(other patent value)		-0.226***				
		(0.077)				
rivals' R&D (Hoberg)			-0.415***			
			(0.049)			
Ln Mahalanobis R&D				-2.404***		
				(0.145)		
asinh(other R&D) IV					-0.286***	
					(0.101)	
Citation obsolescence, δ_c						-0.295***
						(0.067)
N	7694	7694	13024	14874	7555	6977
R^2	0.668	0.666	0.585	0.586	0.668	0.672
rivals	NAICS 6-digit	NAICS 6-digit	Market distance	Tech distance	NAICS 6-digit	

Note: Robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All regressions have firm and year fixed effects, and all independent variables are standardized (divided by their standard deviations). Regressions using NAICS industries exclude industries with less than $1 billion ($2017) in total industry R&D.

Table 3. Obsolescence and R&D

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Log R&D				
Citation obsolescence	-0.055***				
	(0.012)				
δ_p =1/patent term		-0.318***			
		(0.011)			
Log revenue			0.621***	0.622***	0.610***
			(0.003)	(0.004)	(0.005)
$\ln(r+\delta_p)$			-0.323***		
			(0.031)		
Predicted $\ln(r+\delta_p)$				-0.402***	
				(0.058)	
asinh(other R&D) IV					-0.230***
					(0.017)
N	38361	26991	26991	7562	7880
R^2	0.275	0.299	0.722	0.739	0.740
Mean implied δ_r					0.280

Note: Robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects are detailed industry x year in columns 1-3 and industry and year in columns 4-5 (discussed below). Citation obsolescence is used in col. 1; the inverse of the patent term is used in columns 2-4, excluding observations with fewer than 5 patents. Column 4 instruments $\text{asinh}(r+\delta_p)$ using the predicted R&D of rival firms in the same industry but in different states; the predictions are based on state and Federal tax costs of R&D (see Appendix). The regression excludes industries with less than $1 billion ($2017) in total industry R&D. Column 5 shows a reduced form version of the regression in column 4.

Table 4. R&D-based Obsolescence [TBD]

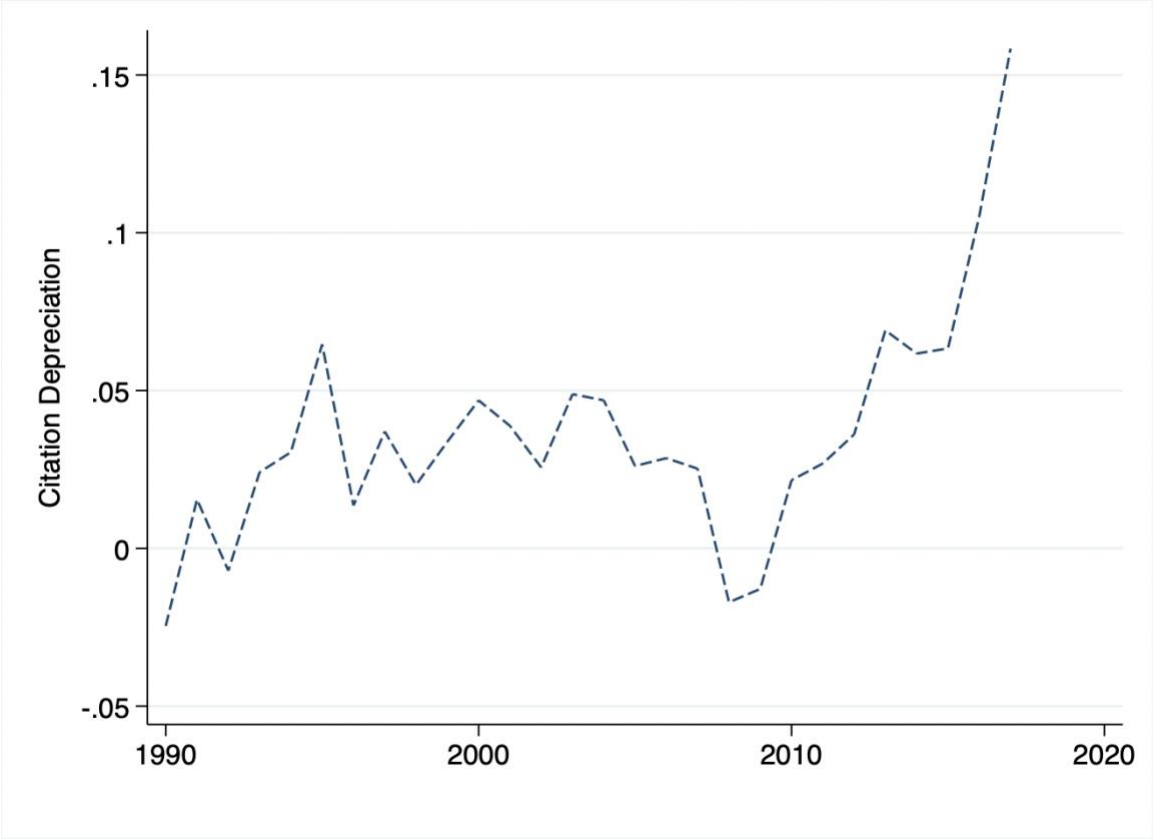
Dependent variable: Log real R&D adjusted for spillovers (see Appendix)

A. Non-farm business sector				
	(1)	(2)	(3)	(4)
Period	1977-1991	1992-1999	2000-2007	2008-2018
Predicted rivals' R&D (asinh)	-0.169	-0.811***	-1.075**	-1.844***
	(0.477)	(0.313)	(0.463)	(0.303)
Log revenue x rivals' R&D (asinh, IV)	-0.016	0.026	0.030	0.083***
	(0.048)	(0.022)	(0.032)	(0.022)
Foreign = 0 x log revenue	0.772***	0.728***	0.650***	
	(0.148)	(0.060)	(0.067)	
Foreign = 1 x log revenue	0.898***	0.784***	0.707***	
	(0.155)	(0.058)	(0.067)	
Log revenue				0.416***
				(0.043)
Adjusted R-squared	0.648	0.74	0.724	0.581
N (rounded)	25000	19500	28500	50000
Mean obsolescence	0.123	0.080	0.239	0.315
	(0.058)	(0.028)	(0.060)	(0.075)
B. Manufacturing Sector				
Predicted rivals' lagged R&D (asinh)	-0.169	-0.811***	-1.075**	-1.844***
	(0.477)	(0.313)	(0.463)	(0.303)
Log revenue x rivals' R&D (asinh, IV)	-0.016	0.026	0.030	0.083***
	(0.048)	(0.022)	(0.032)	(0.022)
Foreign = 0 x log revenue	0.772***	0.728***	0.650***	
	(0.148)	(0.060)	(0.067)	
Foreign = 1 x log revenue	0.898***	0.784***	0.707***	
	(0.155)	(0.058)	(0.067)	
Log revenue				0.416***
				(0.043)
Adjusted R-squared	0.648	0.74	0.724	0.581
N (rounded)	25000	19500	28500	50000
Mean obsolescence	0.123	0.080	0.239	0.315
	(0.058)	(0.028)	(0.060)	(0.075)

Note: Standard errors are shown in parentheses and are clustered by 6-digit industry (*** p<0.01, ** p<0.05, * p<0.10). Obsolescence errors are bootstrapped. Regressions include fixed effects for 6-digit industry and year and use time-consistent sample weights. Rivals' predicted investment is estimated using state and Federal R&D tax cost (see Appendix) 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).

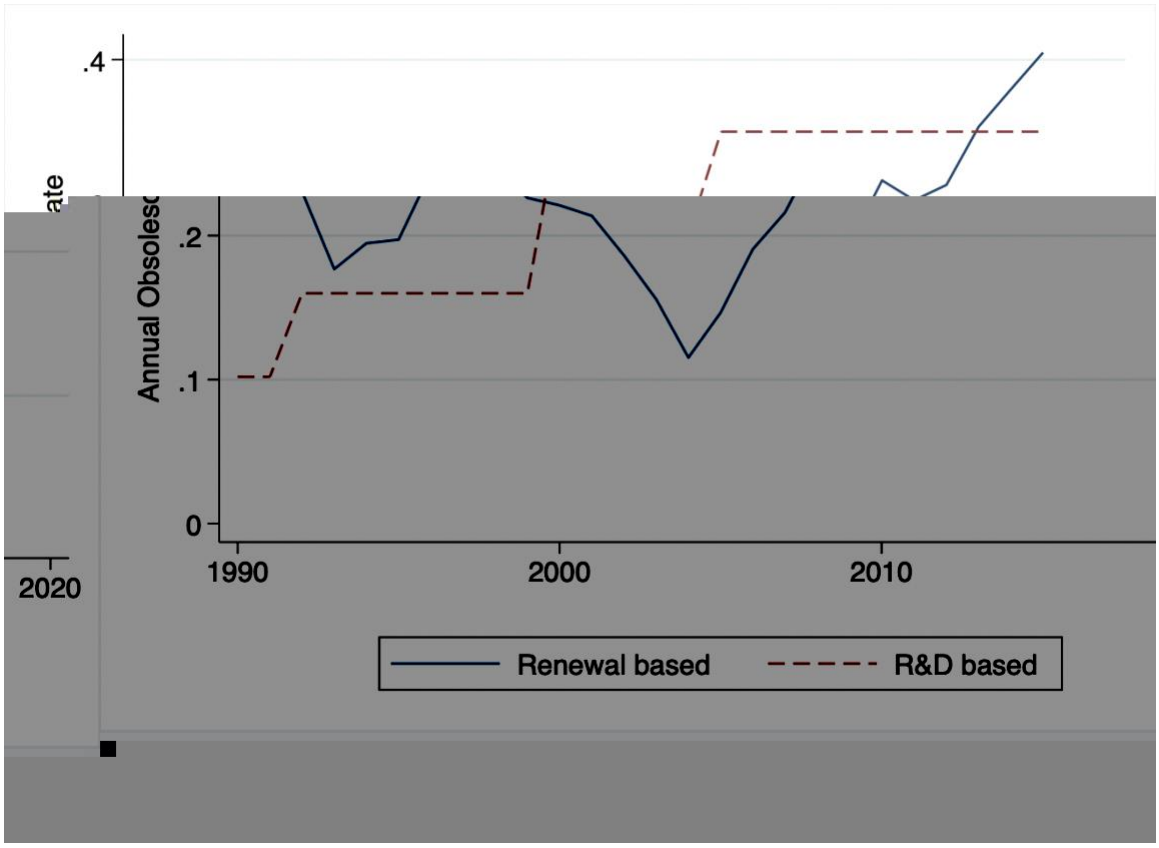
Figures

Figure 1. Mean Citation Obsolescence



Note: Data from Ma (2025) show annualized mean citation obsolescence rate based on a 5 year horizon. The year shown is the year of the technological base.

Figure 2. Renewal and R&D based Obsolescence



Note: Estimates described in the text.

Appendix

Instrumental variable for rivals' R&D

Our regression tables relate obsolescence measures and firm R&D to rivals' R&D. There are endogeneity concerns with both, so we use an instrumental variable approach developed Bloom et al. (2013; see also Lucking et al. 2019) based on predicting rivals' R&D from the different state and Federal tax treatment of R&D that rivals' are subject to. 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. We calculate this tax cost for each state and year. The total Jorgensonian user cost of R&D is then $\rho_{it} P_t^{R\&D}(r_t + \delta)$, where $P_t^{R\&D}$ is the price of R&D services, r_t is the interest rate, and δ is the depreciation rate. We use data on state and federal tax credits developed by Barth et al. (2023). We find that log R&D tax price is a reasonably good predictor of R&D. In the first stage regression, log R&D is regressed on log R&D tax price and firm fixed effects, and the predicted value is used as predicted R&D. We then measure rivals' R&D as the sum of predicted rivals' R&D. For the regressions where log R&D is the dependent variable, we only include rivals' predicted R&D that is conducted in a different state from the focal firm's main R&D lab.

[first stage regression?]

The revenue in equation (9) might also be endogenous. In a supplementary analysis (available from the authors), we predict firm revenue by firm age plus a firm fixed effect. The values of the coefficients on rivals' R&D are similar.

Adjusting for spillovers

We want to use equation (9) to measure the effect of rivals' R&D on focal firm R&D; we expect γ_z to be negative. But rivals' R&D might have a second, positive effect on focal firm R&D from spillovers. That is, technical knowledge developed by rivals might spillover to the focal firm, enhancing its own R&D productivity represented by β in

equation (8). In a related paper we obtain estimates of β by regressing firm productivity against the firm's stock of R&D, following a large literature (Ando et al. 2025b). We measure this spillover effect and adjust the value of log R&D to correct for this positive bias. We do this by regressing firm productivity against the firm R&D stock and an interaction term with the R&D stock and rivals' R&D,

$$\ln TFP_{it} = \beta_0 \ln K_{it} + \beta_S \ln K_{it} \cdot \operatorname{asinh} S_{it} + FE + \epsilon_{it} \qquad (A1)$$

where S_{it} is the sum of rivals' R&D. The TFP measure, the R&D stock, and the weights used in this regression are discussed in the related paper.

Table A1. Measuring the effect of spillovers on R&D output elasticity

[TBD]

Similar estimates are obtained using the flow of R&D rather than the stock. The coefficients on the interaction term are all positive and significant, showing that spillovers tend to increase own-firm R&D productivity. That is, spillovers tend to complement rather than substitute for own firm R&D as other researchers have found (Bloom et al. 2013; W. M. Cohen and Levinthal 1989, 1990). However, the effect is not large, increasing β by about 10 percent at the sample mean (increase shown in the bottom row). In any case, we can use these coefficient estimates to adjust log R&D to back out the effect of spillovers on the dependent variable. The effective output elasticity of R&D in equation (8) is $\beta = \beta_0 + \beta_S \operatorname{asinh} S_{it}$. Since the second term is small, we can use the Taylor series approximation to get $\ln \beta \approx \ln \beta_0 + \frac{\beta_S}{\beta_0} \operatorname{asinh} S_{it}$. Then, backing out the change in $\ln \beta$ in equation (8), we get adjusted log R&D of

$$\ln I_{it}^{*} = \ln I_{it} - \frac{\hat{\beta}_S}{\hat{\beta}_0} \operatorname{asinh} S_{it}.$$

This is done in Table 4. The effect is not large, but it does raise estimates of γ_z and estimated obsolescence rates. Table A2 shows the regression of Table 4 without the adjustment.

Table A.2 R&D demand equation without the spillover adjustment

[TBD]

Table A.3 Renewal-based Patent Obsolescence

	KPSS		Wang		FHK	
1990	0.270	(0.003)	0.248	(0.000)	0.256	(0.223)
1991	0.286	(0.003)	0.264	(0.000)	0.262	(0.227)
1992	0.231	(0.000)	0.210	(0.003)	0.213	(0.055)
1993	0.177	(0.001)	0.158	(0.004)	0.163	(0.125)
1994	0.195	(0.003)	0.175	(0.003)	0.182	(0.119)
1995	0.197	(0.000)	0.180	(0.002)	0.187	(0.114)
1996	0.244	(0.000)	0.222	(0.000)	0.223	(0.108)
1997	0.255	(0.000)	0.232	(0.000)	0.228	(0.105)
1998	0.246	(0.001)	0.224	(0.001)	0.214	(0.107)
1999	0.226	(0.002)	0.206	(0.003)	0.184	(0.109)
2000	0.221	(0.002)	0.201	(0.003)	0.168	(0.048)
2001	0.214	(0.000)	0.194	(0.002)	0.164	(0.047)
2002	0.186	(0.000)	0.166	(0.002)	0.148	(0.111)
2003	0.156	(0.003)	0.136	(0.002)	0.123	(0.106)
2004	0.115	(0.004)	0.097	(0.000)	0.094	(0.106)
2005	0.146	(0.002)	0.127	(0.000)	0.129	(0.112)
2006	0.191	(0.001)	0.170	(0.001)	0.166	(0.118)
2007	0.216	(0.002)	0.195	(0.001)	0.191	(0.046)
2008	0.259	(0.001)	0.235	(0.000)	0.219	(0.100)
2009	0.264	(0.002)	0.241	(0.000)	0.213	(0.109)
2010	0.259	(0.001)	0.235	(0.000)	0.226	(0.109)
2011	0.284	(0.002)	0.259	(0.000)	0.250	(0.113)
2012	0.272	(0.000)	0.248	(0.000)	0.237	(0.112)
2013	0.316	(0.002)	0.292	(0.001)	0.276	(0.110)
2014	0.302	(0.002)	0.280	(0.000)	0.265	(0.048)
2015	0.313	(0.002)	0.290	(0.000)	0.278	(0.117)
2016	0.353	(0.001)	0.329	(0.001)	0.313	(0.121)
2017	0.379	(0.001)	0.354	(0.000)	0.336	(0.122)
2018	0.405	(0.000)	0.386	(0.002)	0.357	(0.050)

Note: Column 1 makes the KPSS assumption that patent value is the stock market reaction times 2.27; Column 2 makes the Wang assumption that the KPSS patent values are overstated by 50 percent; column 3 uses the estimates from Federle et al. (FHK) that allocate stock market returns to individual patents using analysis of how patent characteristics affect patent values in the PATVAL survey.

Table A4. Correlation of obsolescence measures

Dependent variables: firm-year mean values	(1) δ_p = 1/patent term	(2) δ_c = Citation obsolescence
R&D based obsolescence, δ_r	0.010***	0.114**
	(0.002)	(0.049)
N	7880	6987
R^2	0.002	0.001

Note: robust standard errors, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Sample is same as Table 3, column 5.

Figure A1. Renewal Obsolescence Rates under different patent value assumptions

