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# Have R&D Spillovers Changed?

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**Abstract**
This paper revisits the results of Bloom, Schankerman, and Van Reenen (2013) examining the impact of R&D on the performance of US firms, especially through spillovers. We extend their analysis to include an additional 15 years of data through 2015, and update the measures of firms' interactions in technology space and product market space. We show that the magnitude of R&D spillovers appears to have been broadly similar in the second decade of the 21st Century as it was in the mid-1980s. However, there does seem to have been some increase in the wedge between marginal social returns to R&D and marginal private returns with the ratio of marginal social to private returns increasing to a factor of 4 from 3. There is certainly no evidence that the need to subsidize R&D has diminished. Positive spillovers appeared to increase in the 1995-2004 boom.

Key words: innovation, RD, patents, productivity and spillovers.
JEL: O31; O32; O33; F23

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# 1 Introduction

Research and Development (R&D) spillovers have been a major topic in the growth, productivity and industrial organization literatures for many decades. Theoretical studies have explored the impact of research and development (R&D) on the strategic interaction among firms and long run growth.[1] While many empirical studies appear to support the presence of technology spillovers, there remains a major problem at the heart of the literature. This arises from the fact that R&D generates at least two distinct types of "spillover" effects. The first is technology (or knowledge) spillovers which may increase the productivity of other firms that operate in similar technology areas, and the second type of spillover is the product market rivalry effect of R&D. Whereas technology spillovers are beneficial to firms, R&D by product market rivals has a negative effect on a firm's value. Despite a large amount of theoretical research on product market rivalry effects of R&D (including patent race models), there has been very limited econometric work on such effects, in large part because it is difficult to distinguish the two types of spillovers using existing empirical strategies.

It is important to identify the empirical impact of these two types of spillovers. Econometric estimates of technology spillovers in the literature may be severely contaminated by product market rivalry effects, and it is difficult to ascertain the direction and magnitude of potential biases without building a model that incorporates both types of spillovers. Furthermore, even if there is no such bias, we need estimates of the impact of product market rivalry in order to asses whether there is over-

[1] See, for example, Aghion and Howitt (1992) or Spence (1984). Keller (2004), Klenow and Rodriguez-Clare (2005) and Jones (2005) all have recent surveys of the literature.

or under-investment in R&D. If product market rivalry effects dominate technology spillovers, the conventional wisdom that there is under-investment in R&D could be overturned.

One way to address this issue was introduced by Bloom, Schankerman, and Van Reenen (2013), hereafter BSV. Their methodology tried to separately identify two types of research and development (R&D) spillovers: technology spillovers which are beneficial and arise when knowledge flows to the firm from other firms which use similar technologies, and product market rivalry spillovers which are harmful and arise due to business stealing of the firm's competitors. This is accomplished by distinguishing between firms' position in technology space, measured by patenting across technology classes, and position in product market space, measured by sales across four digit industries.

In this paper, we use the BSV methodology to separately identify the technology spillovers and the product market rivalry effects of R&D and reexamine the effect of R&D spillovers on several firm outcomes (market value, patenting, productivity, and R&D). Our panel data includes nearly three times as many firms as BSV because of updates to the underlying data sources and the passage of time. The magnitudes of spillovers are quite similar to those reported in BSV. We find large statistically significant technology spillovers and smaller product market rivalry effects. Interestingly, and in contrast to the earlier results, we find that R&D of firms' product market rivals reduces patenting. We also find somewhat stronger evidence of strategic complementarity in R&D among firms. Finally, we use our estimates to conduct a welfare analysis, showing that the marginal social return to R&D (57.7%) exceeds the marginal private return to R&D (13.6%) by 44.1%. We then show how our estimates of constant technology spillovers can be reconciled with endogenous growth models in which technological innovation is the main driver of economic growth.

The original BSV paper built on a long line of research, perhaps most saliently the work of Griliches (1992). Many authors have subsequently extended this approach. Manresa (2015) generalizes the approach to modeling spillovers in a modified panel data "Pooled" Lasso approach. Lychagin et al. (2015) take a semi-parametric approach and introduce a third spillover aspect based on geographical closeness, which they show is independently important. Colino (2017) adds a dynamic spillover measure which takes into account when past R&D may create future spillovers using citation information (finding this particularly important in industries with complex products that build cumulatively on multiple components).

The rest of the paper is organized as follows. First, we describe the data and measurement of key variables, including the measures of technological proximity and product market proximity which are central to the analysis. Next, we review the econometric framework and theoretical predictions of the BSV model of firms' production, patenting, and knowledge production. We then present the estimation results and conduct a welfare analysis. Finally, we show our estimates are consistent with endogenous growth models and in particular with recent papers studying the productivity slowdown, before concluding with a few remarks.

# 2 Data

In this section we discuss the construction of our dataset, highlighting where updates have been made to the BSV data. The complete dataset and all replication files are available online at https://people.stanford.edu/nbloom/research.

## 2.1 Sample Construction

We combine three primary data sources to create the analysis sample. First, data on firm patenting and patent citations are from the NBER Patent Data Project.[2] The NBER patent data includes data from the U.S. Patent and Trademark Office (USPTO) on the universe of utility patents granted between 1976 and 2006 in addition to firm identifiers (gvkey) which allow matching patent data to accounting data from Compustat. Updates to the NBER patent data allow us to significantly increase the sample of patenting firms for two reasons. Whereas BSV included utility patents which had been granted by 1999, recent updates allow us to include patents granted through 2006. In addition, the NBER's match of patent assignee to the Compustat firm identifier "gvkey" has been improved, allowing us to identify more patenting firms throughout the entire period of analysis.

Second, we use the Compustat Segments database which breaks down firm sales by line of business. Each line of business is associated with a primary industry code (4-digit SIC), and in many cases a secondary industry code. For lines of business with two codes listed, we allocate 75 percent of the line's sales to the primary industry and 25 percent to the secondary industry. We use Compustat Segments data from 1980

[2] https://sites.google.com/site/patentdataproject/Home

through 2015, whereas BSV used Segments data from 1993 through 2001. Finally, we merge both the patent data and the line of business data to accounting data (sales, employment, R&D, market value, etc.) for 1980 through 2015 from the Compustat Fundamentals database.

## 2.2 Measuring Technological Proximity

Technological proximity is measured using the Jaffe (1986) metric as well as the Mahalanobis generalization introduced in BSV. Both measures describe the correlation of patenting across USPTO technology classes between pairs of firms. To calculate technological proximity, we first allocate all of the firm's patents between 1970 and 2006 into the different USPTO technology classes, defining for firm $i$ the vector $T_i = (T_{i1}, T_{i2}, ...T_{i426})$ where $T_{i\tau}$ is the share of firm $i$'s patents in technology class $\tau$. The Jaffe (1986) measure of technological proximity between firm $i$ and firm $j$ is given by:

$$TECH_{ij} = \frac{(T_i T_j')}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}}. \tag{1}$$

The pool of technology spillovers to firm $i$ in year $t$, $SPILLTECH_{it}$, is the the stock of R&D of all the firms with which firm $i$ interacts in technology space, weighted by the Jaffe (1986) measure of technological proximity. Specifically,

$$SPILLTECH_{it} = \sum_{j \neq i} TECH_{ij} G_{jt}, \tag{2}$$

where $G_{jt}$ if firm $j$'s stock of R&D in year $t$.

## 2.3 Measuring Product Market Proximity

Product market proximity is measured using line of business data from the Compustat Segment Dataset, which provides each firm's sales disaggregated by four digit industry code. We begin by defining the vector $S_{it} = (S_{i1t}, S_{i2t}, ..., S_{i473t})$, where $S_{ikt}$ is the share of firm $i$'s sales in industry $k$ from year $t-5$ to year $t-1$. Rather than pool across all years to construct firm industry sales share, we pool the previous five years of data. Pooling the segments data across all 35 years is problematic in this setting. Future industry sales shares are clearly endogenous as firm innovation and R&D affects subsequent product market success. Past sales shares do not suffer from endogeneity but will be mismeasured if firms move in product space over time. While the results in BSV are robust to using lagged, future or pooled segments data, our data cover a much longer time period which likely exacerbates the endogeneity and measurement problems introduced by pooling the data. We therefore use the 5 previous years of firm sales in order to (a) minimize reverse causality between firm outcomes and product market competition and (b) accurately measure the firm's time $t$ location in product market space. The results do not appear sensitive to this choice – using the firm's previous 10 years or 20 years of sales produces similar estimates. Product market proximity is measured by the correlation of firms' sales across four digit industries:

$$SIC_{ij} = \frac{(S_i S_j')}{(S_i S_i')^{1/2}(S_j S_j')^{1/2}}. \tag{3}$$

The pool of product market spillovers to firm $i$ in year $t$, $SPILLSIC_{it}$, is the stock of R&D of all the firms with which firm $i$ interacts in product market space, weighted by our measure of product market proximity. Specifically,

$$SPILLSIC_{it} = \sum_{j \neq i} SIC_{ij} G_{jt}, \tag{4}$$

## 2.4 Mahalanobis Extension

We also construct alternatives versions of $SPILLTECH$ and $SPILLSIC$ using the Mahalanobis distance metric. This measure allows for spillovers between different technology classes, which is ruled out by the Jaffe metric (which assumes full spillovers within the same class and nothing otherwise). In summary, Mahalanobis measures cross technology class spillovers by using revealed preference. If two technologies are often located together in the same firm (e.g. "computer input/output" and "computer processing") then we infer the distance between the technologies is smaller, so spillovers will be greater. We proxy this by the share of times the two technology classes are patented within the same firm.

To explain the exact calculation of the Mahalanobis normed measure we require additional notation. First, we let $T = [T_1', T_2' ... T_N']$ denote the $(426, N)$ matrix where each column contains a firm's patent shares in the 426 technological classes. Second, we define a normalized $(426, N)$ matrix $\tilde{T} = [T_1'/(T_1 T_1')^{1/2}, T_2'/(T_2 T_2')^{1/2} ... T_N'/(T_N T_N')^{1/2}]$, in which each column is simply normalized by the firm's patent share dot product. Third, we define the $(N \times N)$ matrix $TECH = \tilde{T}'\tilde{T}$. This matrix $TECH$ is just the standard Jaffe (1986) uncentered correlation measure between firms $i$ and $j$, in which each element is the measure $TECH_{ij}$, exactly as defined in equation 1 above. Fourth, we define a $(N, 426)$ matrix $\widetilde{X} = [T'_{(:,1)}/(T_{(:,1)}T'_{(:,1)})^{1/2}...T'_{(:,426)}/(T_{(:,426)}T'_{(:,426)})^{1/2}]$ where $T_{(:,i)}$ is $(1, N)$ and is the $i^{th}$ row of $T$. This matrix $\widetilde{X}$ is similar to $\widetilde{T}$, except it is the normalized patent class shares across firms rather than firm shares across patent classes. Finally, we can define the $(426, 426)$ matrix $\Omega = \widetilde{X}'\widetilde{X}$ in which each element is the standard Jaffe (1986) uncentered correlation measure between patent classes (rather than between firms). So, for example, if patent classes $i$ and $j$ coincide frequently within the same firm, then $\Omega_{ij}$ will be close to 1 (with $\Omega_{ii} = 1$), while if they never coincide within the same firm $\Omega_{ij}$ will be 0.

The Mahalanobis normed technology closeness measure is defined as $TECH^M = \widetilde{T}'\Omega\widetilde{T}$. This measure weights the overlap in patent shares between firms by how close their different patents shares are to each other. The same patent class in different firms is given a weight of 1, and different patent classes in different firms are given a weight between 0 and 1, depending on how frequently they overlap within firms across the whole sample. Note that if $\Omega = I$, then $TECH^M = TECH$. Thus, if no patent class overlaps with any other patent class within the same firm, then the standard Jaffe (1986) measure is identical to the Mahalanobis norm measure. On the other hand, if some patent classes tend to overlap frequently within firms - suggesting they have some kind of technological spillover - then the overlap between firms sharing these patent classes will be higher.

## 2.5 Sample and Descriptive Statistics

To be included in our sample firms must have segments and accounting data at some time between 1980 and 2015, and must have applied for a patent at some point between 1970 and 2006. We also drop firms with less than 4 years of data and with large jumps in sales and employment in consecutive years, which may be indicative of M&A activity. We exclude the first 5 years of data (1980-1984) from all regressions in order to construct the knowledge stock measures. Table 1 contains summary statistics for several key variables for the 1,985 firms in our sample in columns 1-3, and for the sample in BSV in columns 4-6. Summary statistics are presented over the period from 1981 to 2001 to facilitate comparison between the two samples. Compared to BSV, the firms in our sample have higher Q, are more R&D-intensive measured by R&D stock, flow, and stock scaled by physical capital, and they patent more often. Our firms are on average smaller in terms of market value, sales, physical capital, and employment than the firms in the old BSV sample because the increased match sample included many medium and smaller Compustat firms.

# 3 Econometric Framework

We are interested in estimating the effects of R&D spillovers and product market rivalry on four firm outcomes: market value, R&D spending, productivity, and citation-weighted patenting. Theory has clear predictions for the first two firm outcomes, while productivity and patenting are used to proxy for knowledge. Market value should be increasing in the size of the pool of R&D spillovers from technologically similar firms ($SPILLTECH$) and decreasing in the size of the pool of spillovers from product market rivals ($SPILLSIC$). Patenting and productivity should be increasing in $SPILLTECH$. Lastly, the theoretical predictions for the effects of spillovers on R&D vary depending on whether R&D undertaken by firms' product market rivals is a strategic substitute or a strategic complement. R&D is increasing in $SPILLSIC$ in the case of strategic complements and decreasing in the case of strategic substitutes. The relationship between R&D and $SPILLTECH$ is ambiguous because it depends on how technology spillovers affect the firm's marginal product of R&D.

## 3.1 Market Value Equation

We estimate the effect of R&D spillovers on market value in the following specification:

$$
\begin{aligned}
\ln(Q_{it}) = {} & \gamma_1 \phi[\ln\left(\frac{G}{A}\right)_{it-1}] + \gamma_2 \ln SPILLTECH_{it-1} + \gamma_3 \ln SPILLSIC_{it-1} \\
& + \gamma_4 X_{it}^V + \eta_i^V + \tau_i^V + \nu_{it}^V,
\end{aligned} \tag{5}
$$

where $Q_{it}$ is Tobin's Q, $\phi[\left(\frac{G}{A}\right)_{it-1}]$ is a function of the lagged R&D stock divided by the stock of non-R&D assets (which we will approximate by a sixth order polynomial), $X_{it}^V$ is a vector of time-varying controls, and $\eta_i^V$ and $\tau_i^V$ are firm and year fixed effects respectively.

## 3.2 Patent Equation

We estimate a negative binomial of citation-weighted patents:

$$
\begin{aligned}
P_{it} = \exp(&\lambda_1 \ln G_{it-1} + \lambda_2 \ln SPILLTECH_{it-1} + \lambda_3 \ln SPILLSIC_{it-1} \\
&+ \lambda_4 X_{it}^P + \eta_i^P + \tau_i^P + \nu_{it}^P),
\end{aligned} \tag{6}
$$

where $P_{it}$ is future citations weighted patents for firm $i$'s patents applied for in year $t$ and $G_{it-1}$ is lagged R&D capital stock. The firm fixed effect $\eta_i$ is measured as the pre-sample average citation-weighted patents. One concern with using citations-weighted patents is that more recently issued patents have had less time to garner citations than older patterns. We address this by including year fixed effects in all specifications.

### 3.3 Productivity Equation

The production function is Cobb-Douglas in R&D capital, labor, and non-R&D capital, with additional terms for R&D spillovers:

$$
\begin{aligned}
\ln Y_{it} = &\psi_1 \ln g_{it-1} + \psi_2 \ln SPILLTECH_{it-1} + \psi_3 \ln SPILLSIC_{it-1} \\
&+ \psi_4 X_{it}^Y + \eta_i^Y + \tau_i^Y + \nu_{it}^Y),
\end{aligned} \tag{7}
$$

where $Y_{it}$ is real sales, $X_{it}$ includes labor and capital, and $\eta_i^Y$ and $\tau_i^Y$ are firm and year fixed effects.

### 3.4 R&D Equation

R&D factor demand is:

$$\ln\left(\frac{R}{Y}\right)_{it} = \alpha_2 \ln SPILLTECH_{it-1} + \alpha_3 \ln SPILLSIC_{it-1} \\ + \alpha_4 X_{it}^R + \eta_i^R + \tau_i^R + \nu_{it}^R, \tag{8}$$

where $R_{it}$ is the flow of R&D spending.

## 4 Results

The estimates of the market value equation are presented in Table 2. All specifications, in this table and throughout the paper, include year and firm fixed effects. In column (1) we present the estimates from BSV for comparison. In column (2) we find a strong positive relationship between $SPILLTECH$ and market value and a strong negative relationship between market value and $SPILLSIC$. R&D by technologically similar firms increases firm value.[3] Conversely R&D by firms' product market rivals reduces firm value. Interestingly these coefficient estimates are remarkably similar to those reported in BSV and reproduced in column (1). In columns (3) and (4) we include only the technology spillover or the product market competition spillover, and the estimated spillover effects are somewhat smaller but overall very similar. Column (5) uses the Mahalanobis metric to measure the distance be-

[3]The ln(R&D/capital) coefficient reported in Table 2 is the implied elasticity of market value with respect to R&D/capital evaluated at the sample mean R&D/capital ratio. Standard errors are calculated using the delta method.

tween firms in product market space. Recall that while the Jaffe measure imposes zero spillovers across different technology classes (industries) for $TEC$ ($SIC$), the Mahalanobis metric allows for these inter-class (inter-industry) spillovers by using the empirical co-patenting (co-sales) rates to measure the distance between different technology classes (product markets). Using the Mahalanobis metric increases the coefficient estimates of both spillovers measures by roughly 60 percent in absolute magnitude. Finally, in Column (6) we estimate the market value equation using R&D tax credits to instrument for $SPILLTEC$ and $SPILLSIC$. While the relationship between product market spillovers and market value is essentially unchanged compared to our preferred specification with the Jaffe metric and firm fixed effects in column (2), the positive association between technology spillovers and market value falls by two-thirds. This suggests there could be a positive bias possibly because market value shocks to a technology sector leads all firms to increase innovation.

Table 3 displays the estimates of the patent equation. In column (2) we regress cite weighted patents (using a negative binomial count data model) on our two spillovers measures, the R&D stock, a firm pre-sample fixed effect which controls for the firm's average citation weighted patents in the pre-sample period[4], and lagged patents. Unsurprisingly, the coefficient on ln(R&D Stock) confirms that firms with more R&D capital produce more patents. We find a somewhat smaller positive relationship between $SPILLTECH$ and patenting compared to BSV, and a negative relationship between $SPILLSIC$ and patenting in contrast to BSV's finding of no significant relationship. Omitting either $SPILLSIC$ in column (3) or $SPILLTEC$

[4]The pre-sample period is defined as the 5 years before the firm enters the regression sample.

in column (4) attenuates the remaining spillover coefficients slightly. The estimates using the Mahalanobis measure and the Jaffe measure with instrumental variables are quantitatively similar to the fully specified model in (2).

Table 4 summarizes the estimates of the production function. Comparing column (1) and column (2), the results on our new sample are similar to the old estimates, although we find slightly larger positive effects of technology spillovers on productivity. There is no significant relationship between product market spillovers and productivity, with the coefficient on log $SPILLSIC$ estimated precisely and close to zero. The inputs in production – labor, physical capital, and R&D capital – enter the production function positively and significantly. The productivity effects are similar when we use the Mahalanobis measure in column (5) or use tax credit instruments in column (6).

The R&D-intensity estimates are summarized in Table 5. We find a positive relationship between both types of spillovers and R&D-intensity. In our preferred specification a 10% increase in $SPILLTEC$ is associated with an 12.5% increase in R&D-intensity; a 10% increase in $SPILLSIC$ is associated with a 5.4% increase in R&D-intensity.

In summary, our updated estimates are similar to the findings in BSV with one exception - our finding in Table 3 of a strong negative relationship between firm patenting and R&D of the firm's product market competitors. This can be rationalized in a model with endogenous patenting decisions. The intuition is that R&D by firm's competitors reduces the marginal benefit of R&D and thus the firm's propensity to patent.[5]

## 5 Changes over time

In this section we assess how the spillovers estimates have changed over time by allowing the coefficients of interest in equations 5, 6, 7, and 8 to vary over time. This allows us to distinguish between the extent to which changes in the coefficient estimates are due to a changes in the underlying sample and data versus changes in the nature of spillovers over time. The estimates are broadly stable over time although there do appear to be some significant changes in the spillovers parameters around the time of the late 1990s dot-com boom and some evidence of changes in the returns to R&D in recent years. In the following paragraphs we discuss the estimates from each equation in turn.

In Table 6 we assess how the R&D coefficients have changed over time in the market value regressions. We re-estimate 5 and interact dummy variables for each 5-year time period with the technology spillover variable, the product market spillover variable, and firm R&D/capital (note that the period 1985 to 1989 is the baseline 5-year period).[6] Columns 1, 2, and 3 shows the time-varying estimates of the coefficient on technology spillovers, product market spillovers, and R&D/capital, respectively. Estimated technology spillovers and product market rivalry effects in columns 1 and 2 are quite stable over time, with one notable exception. Positive technology

[5]See BSV Appendix A.3.

[6]For this exercise we only include the the first-order term of firm R&D/capital, omitting the higher-order terms in 5. Including the second through sixth order terms with each of the five-year time period dummies would require estimating an additional 30 coefficients.

spillovers were 48% larger and negative product market rivalry effects 38% smaller on average during the ten years encompassing the dot-com boom of 1997-2001.[7] Before and after the dot-com boom, the estimates are very flat over time and we find no statistically significant changes in the spillovers estimates over time. In contrast to the stable estimates of spillovers, the returns to R&D appear to be decreasing over time, especially in the last 15 years of the sample. The estimated returns to R&D are 14% lower from 2000 to 2004 compared to 1985-1989, and the difference is significant at the 10% level. In the next 5 years from 2005 to 2009 the estimated returns are 27% lower, and in the last five years from 2010 to 2015 they are 37.4% lower, with both differences again relative to the 1985-1989 estimates and significant at the 1% level.

Table 7 allows the coefficients in the Patent equation to vary over time. The results in Table 7 also suggest higher knowledge spillovers and lower product market rivalry effects from 1995 to 2004. However since our patent dataset ends in 2005 it is difficult to identify trends in the estimated coefficients, and more so to distinguish between a possibly temporary relationship during the dot-com boom versus longer term trend.

The time-varying estimates for the Productivity equation are presented in Table 8. Again the estimates are reasonably stable over time. In contrast to the Market Value Equation, there is much less evidence of an effect of the dot-com boom on estimated technology spillovers. Aside from a small statistically significant increase from 1995 to 1999, we find no change in the technology spillovers parameter over

[7] For technology spillovers: 0.5*(0.115+0.112)/0.237=0.478. For product market rivalry: 0.5*(0.019+0.042)/0.081=0.377.

time. The estimate of the coefficient on ln(SPILLSIC) is also quite stable over time. Except for the first 5 years of the sample, 1985-1989, the estimated coefficient on ln(SPILLSIC) is always statistically indistinguishable from zero.

Finally, we examine how the estimates of the R&D equation have changed over time in Table 9. In contrast to the earlier results, the coefficients on ln(SPILLTEC) and ln(SPILLSIC) do appear to be trending over the past 30 years. In particular the estimated coefficient on ln(SPILLTEC) has decreased over the sample, especially in the past 10 years, suggesting less strategic complementarity among technologically similar firms. Indeed in the last 5 years of the sample we cannot reject the null hypothesis that the coefficient on ln(SPILLTEC) is equal to zero. Conversely, the coefficient on ln(SPILLSIC) have been trending up over time. There is no statistically significant relationship between product market spillovers and own R&D from 1985 through 1994, while from 1995 through 2015 we do find evidence of positive and increasing strategic complementary of R&D among product market rivals.

To summarize the results from this section, the estimates of technology and product market spillovers have been quite stable for the 30 years in our sample. From 1995 to 2005 we find greater technology spillovers and smaller negative product market spillovers. This is strongest in the market value equation regressions with log(Tobin's Q) as the dependent variable, but present in the patent and productivity equations as well. Our interpretation is that this reflects the market exuberance for high-R&D firms around the time of the dot-com boom. We also see increasing strategic complementarities in R&D among product market rivals, and decreasing strategic complementarity among technologically similar firms.

# 6 Welfare implications

What do these estimates imply about the marginal social return to R&D? We conduct a simple welfare analysis as in BSV to determine how the updated results affect estimates of the marginal private return (MPR) to R&D and the marginal social return (MSR). The marginal private return measures the change in firm output due to an increase in firm R&D, and the marginal social return measures the change in aggregate output due to an increase in firm R&D. Under certain simplifying assumptions.[8], BSV show that we can calculate the marginal private return as

$$MPR = \frac{Y}{G}(\psi_1 - \sigma\gamma_1), \tag{9}$$

where $\sigma$ is the share of the reduction in market value which is due to a decline in output as opposed to a decline in price and is assumed to be one half, $\gamma_1$ is the the elasticity of market value with respect to $SPILLSIC$, and $\psi_1$ is the elasticity of output with respect to the R&D stock.

Similarly, the marginal social return can be calculated as

$$MSR = \frac{Y}{G}(\psi_1 + \psi_2), \tag{10}$$

where $\frac{Y}{G}$ is the ratio of output to the R&D stock, $\psi_1$ is the elasticity of production with respect to R&D stock and $\psi_2$ is elasticity of production with respect to the technology spillovers $SPILLTEC$. The formula for MSR captures the effect of

[8]Specifically, if all firms are the same in terms of their sales and R&D stock, all firms have the same linkages with other firms in technology and product market spaces, and the coefficients estimated in the previous sections are causal.

increasing R&D on the firm's own output through $\psi_1$ and it's effect on other firms through $\psi_2$.

Evaluating the marginal social return at the median output to R&D stock ratio (2.345), MSR=2.345*(0.015+0.231)=0.577, or 57.7%. Similarly, the marginal private return evaluated at the median ratio of output to R&D stock is MPR=2.345*(0.015-0.5*(-0.086))=0.136, or 13.6%. That is, we find that under this simple calculation the social return to R&D greatly exceeds the private return, by 44.1%. Compared to the original results, we find a similar marginal social return (57.7% versus 55.0%) and a smaller private return (13.6% versus 20.7%). The smaller private return is due to a smaller output elasticity with respect to R&D capital ($\psi_1$) as our estimate of the elasticity of market value with respect to product market rivalry ($\gamma_1$) is very similar to the original results. Meanwhile, our estimate of a very similar social return to R&D reflects the fact that our lower estimate of $\psi_1$ is closely offset by the higher estimated output elasticity with respect to technology spillovers ($\psi_2$). In short, the ratio of social to private returns has increased from a factor of 3 in BSV to a factor of 4.

We can also analyze how the marginal social return of R&D has changed over time using our time-varying estimates of the spillovers coefficients from Tables 6 through 9. Note that the MSR is equal to the sum of the production elasticities $\psi_1$ and $\psi_2$ divided by the R&D stock as a share of GDP. In calculating the marginal social return above, we have used the median R&D to sales ratio in our sample of Compustat firms as our estimate of the R&D stock as a share of GDP. On the one hand this is a natural choice as it is an accurate measure for the sample of firms on which we have estimated the spillovers parameters, with the median chosen to reduce the influence of outlier firms. On the other hand, our sample necessarily contains R&D-intensive, publicly listed firms and so using this perhaps unrepresentative measure of changes in the R&D stock-GDP ratio over time may lead us to mischaracterize the evolution of the MSR. Thus, we also compare our estimates of the MSR to a version which uses the aggregate ratio of US business enterprise R&D ("BERD") stock to GDP ratio (from OECD data) instead of the Compustat median R&D.[9]

Figure 1 plots the evolution of the MSR from 1985 through 2015. The solid black line shows the MSR setting Y/G to the year-specific median Compustat R&D stock divided by sales. The MSR is similar in 2015 to 1985 at around 0.63 at the beginning and 0.60 at the end. In between, it dipped somewhat at the end of the 1990s but then rose again in the following 15 years. The dotted line sets Y/G equal to the aggregate business R&D stock divided by GDP and is normalized to have the same level as the Compustat measure in 1985 to highlight changes in the series over time. This measure rises through the mid-1990s and gently falls thereafter. By 2015 the series returned to roughly the same level as in 1985. Since the coefficients we use are the time-varying values from Tables 6 and 8, the differences in the two lines are generated solely by the different paths of the R&D to output ratios in the two sources. Overall, there is no strong pattern upwards or downwards and we conclude

[9] There are many differences between the two measures in addition to using the median vs. the (weighted) mean. First, BERD is based on R&D conducted in the US regardless of whether it is by US listed firms or foreign branches of multinationals. Compustat R&D is the global amount of R&D by a US-listed firm even if this is conducted overseas. Second, BERD includes firms who are not publicly listed. Third, the exact definitions vary with Compustat based on GAAP accounting regulations and BERD based on the Frascati manual definition. Fourth, whereas a firm's Compustat R&D is publicly available, the firm-level data from BERD surveys are not publicly available.

that the MSR has been broadly stable over this 30 year period.

# 7 Relationship with endogenous growth models

An interesting question is how do our estimates of R&D spillovers reconcile with standard endogenous growth models? Bloom et al. (2017) note that many new growth models can be described by a steady state or ideas growth equation of the form:

$$\frac{\dot{A}}{A} = \pi R, \tag{11}$$

where these are economy-wide values. This implies that ideas growth ($\frac{\dot{A}}{A}$) is proportional to a measure of research effort $R$. $\pi$ can be thought of as a measure of research productivity - it is the degree to which an absolute given amount of research effort translates into growth. These models imply that constant research effort should lead to constant exponential growth. [10] Unfortunately, equation (11) is not easily reconcilable with the data as the number of US researchers has increased substantially over time whereas US TFP growth rates have not. Alternatively, semi-endogenous growth models (e.g. Jones, 1995; Kortum, 1997) allow for diminishing returns to research productivity ($\beta \geq 0$ ):

$$\frac{\dot{A}}{A} = \alpha A^{-\beta} R. \tag{12}$$

[10] For example, in Romer (1990) what is defined here as R is called $H_A$, or "total human capital employed in research."

The pure endogenous growth model (e.g. Romer, 1990) is when $\beta = 0$ so $\pi = \alpha$.[11]

In our framework, the ideas stock is given by the aggregate R&D knowledge stock, which is a combination of firm-level $G$ and the aggregation of $SPILLTECH$. The economy-wide production function can be written:

$$Y = A^{\sigma} K^{1-\beta_L} L^{\beta_L} \tag{13}$$

with $0 < \sigma \leq 1$ . The marginal social return to the R&D knowledge stock is:

$$\frac{dY}{dA} = \sigma \frac{Y}{A} \tag{14}$$

If we assume that at the aggregate level there is little depreciation of the knowledge stock, research effort $R$ can be thought of as the change in the economy's knowledge stock, $\dot{A}$. [12] The change in the ideas stock is then simply:

$$\dot{A} = R. \tag{15}$$

which implies that the growth rate of ideas ($g_A = \frac{\dot{A}}{A}$) is:

$$g_A = \frac{\dot{A}}{A} = \frac{R}{A}$$

or

[11] Note that we could change $R$ in equation (12) to $R^{\lambda}$ where $0 < \lambda \leq 1$ to allow for "stepping on toes" effects of duplicative research, but we keep to $\lambda = 1$ for simplicity due to the disagreement in the literature of what an appropriate value should be (see Bloom et al. 2017 for a discussion).

[12] The private knowledge stock is likely to depreciate as firms copy each other and old R&D is made obsolete. But as Griliches (1992) argued the social knowledge stock depreciation will be substantially lower and possibly zero.

$$A = R/g_A \tag{16}$$

Substituting this expression for $A$ back into the MSR formula (14) gives:

$$\frac{dY}{dA} = \sigma \frac{g_A}{(R/Y)} \tag{17}$$

Equation (17) shows that the MSR is determined by the degree of diminishing returns to the idea stock ($\sigma$), the fundamental growth rate of new ideas ($g_A$, which in semi-endogenous growth models is not affected by R&D in the long run) and the R&D to GDP ratio ($R/Y$). A more general derivation of equation (17) is in Jones and Williams (1998) - see their equation (16) for example.

Our finding of a broadly stable social return to the US R&D stock in the last 35 years (Figure 1) is consistent with the stability of the objects on the right hand side of equation (17). This conclusion might seem surprising in the light of the evidence in Bloom et al. (2017) that research productivity as measured by $\pi$ in equation (11) has been *declining* over time. But this evidence is consistent with what we would expect when growth can be described by equation (12) and $\beta \approx 1$, as research productivity, $\pi_t$ is falling over time as $A_t$ grows. Growth would have slowed by a lot more had $R$ stayed constant, but in fact $R/Y$ has stayed broadly constant which is the same as saying R&D has risen as the economy has grown and this offsets the fall in $\pi$. This conclusion echoes Jones and Williams (1998) who showed the consistency between the social returns estimates in the micro productivity literature (which we broadly follow) and more formal macro endogenous growth models (as investigated in Bloom et al, 2017).[13]

## 8 Conclusion

This paper has updated the results of Bloom, Schankerman and Van Reenen (2013). We include an additional 15 years of data in our analysis of the effects of spillovers on firm value, productivity and R&D, and an additional 6 years of data in our analysis of the effects of spillovers on firm patenting, increasing our sample size by two to three fold. The updated estimates are broadly similar to the original findings. We show that there are large positive spillovers among technologically-close firms, and negative spillovers from product market rivals due to the business stealing effect. In contrast to Bloom, Schankerman and Van Reenen (2013) we find a negative effect of rivals' R&D on firm knowledge production as measured by citation-weighted patents. Back-of-the-envelope welfare calculations confirm the earlier paper's findings of a sizable wedge between the social and private returns to R&D. Indeed, our estimates suggest that the wedge may be even larger.

The additional data also allows us to explore the changing natures of technology and product market spillovers over time. Perhaps surprisingly, we find that estimated spillovers are remarkably stable over the three decades we study. There are several exceptions, most notably elevated technology spillovers around the time of the dot-com boom of 1997-2001 which may reflect market enthusiasm for R&D-intensive

[13] Jones and Williams (1998) show how the kind of social returns to R&D estimates built from R&D augmented Cobb-Douglas production function like equation (7) relate to the formal semi-endogenous growth models reflected in equation (12). In short, a log-linearized approximation of the production function for ideas (12) around the steady state growth path can be mapped into our estimate of the social rate of return.

firms, however the broad finding is of relatively unchanging spillovers from both technologically close firms and firms which are close competitors in terms of product markets. Finally, we show how our framework for estimating welfare implications of R&D spillovers, in which we find a roughly constant marginal social return to R&D over the past thirty years, can be reconciled within the framework of a standard semi-endogenous growth model.

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Table 1: Summary Statistics

| | New Sample | | | Old Sample | | |
|---|---|---|---|---|---|---|
| | **Median** | **Mean** | **S.D.** | **Median** | **Mean** | **S.D.** |
| **Tobin's Q** | 1.77 | 3.3 | 4.17 | 1.41 | 2.36 | 2.99 |
| **Market Value** | 255 | 4,053 | 15, 946 | 412 | 3,913 | 16,517 |
| **R&D Stock** | 43.3 | 863.4 | 3,491 | 28.7 | 605 | 2,722 |
| **R&D Stock/Capital** | 0.4 | 0.97 | 1.68 | 0.17 | 0.47 | 0.91 |
| **R&D Flow** | 6.96 | 145 | 586 | 4.36 | 104 | 469 |
| **Technology Spillovers** | 50,679 | 70,902 | 65,801 | 20,091 | 25,312 | 19,942 |
| **Prod. Market Spillovers** | 20,066 | 38,145 | 49,284 | 2,007 | 6,494 | 10,114 |
| **Patent Flow** | 1 | 26.2 | 134.5 | 1 | 16.2 | 75 |
| **Cite-weighted patents** | 5 | 179 | 698 | 4 | 116 | 555 |
| **Sales** | 210.38 | 3,897 | 24,560 | 456 | 2,879 | 8,790 |
| **Physical Capital** | 49.2 | 1,180 | 4,990 | 122 | 1,346 | 4,720 |
| **Employment** | 1,700 | 15,169 | 43,424 | 3,839 | 18,379 | 52,826 |

**Notes:** The means, medians, and standard deviations are taken over all non-missing observations between between 1981 and 2015 for Columns 1 through 3 and between 1981 and 2001 for Columns 4 through 6. Columns 1 through 3 include the new analysis sample which contains 1,985 firms. Columns 4 through 6 present summary statistics for the sample of 705 firms in Bloom, Schankerman, and Van Reenen (2010).

Table 2: Market Value Equation

| | Old Sample | New Sample | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| | **OLS** | **OLS** | **OLS** | **OLS** | **OLS** | **IV** |
| | **Jaffe** | **Jaffe** | **Jaffe** | **Jaffe** | **Mahalanobis** | **Jaffe** |
| **ln(SPILLTECH)** | 0.381*** | 0.324*** | 0.284*** | | 0.519*** | 0.102* |
| | (0.113) | (0.04) | (0.04) | | (0.05) | (0.056) |
| **ln(SPILLSIC)** | -0.083*** | -0.086*** | | -0.066*** | -0.135*** | -0.085*** |
| | (0.032) | (0.013) | | (0.013) | (0.019) | (0.023) |
| **ln(R&D/Capital)** | 0.496** | 0.324*** | 0.321*** | 0.331*** | 0.319*** | 0.339*** |
| | (0.069) | (0.022) | (0.022) | (0.023) | (0.022) | (0.024) |
| | | | | | | **1st Stage F-stat** |
| **ln(SPILLTECH)** | | | | | | 3439.1 |
| **ln(SPILLSIC)** | | | | | | 863.8 |
| **Observations** | 9,944 | 29,688 | 29,688 | 29,688 | 29,688 | 26,403 |

**Notes:** Dependent variable is ln(Tobin's Q) defined as the market value of equity plus debt, divided by the stock of fixed capital. All columns include firm and year fixed effects. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey-West correction. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Patent Equation

| | Old sample | New sample | | | | |
|---|---|---|---|---|---|---|
| | **(1)**<br>**OLS**<br>**Jaffe** | **(2)**<br>**OLS**<br>**Jaffe** | **(3)**<br>**OLS**<br>**Jaffe** | **(4)**<br>**OLS**<br>**Jaffe** | **(5)**<br>**OLS**<br>**Mahalanobis** | **(6)**<br>**IV**<br>**Jaffe** |
| **ln(SPILLTECH)** | 0.417*** | 0.284*** | 0.259*** | | 0.365*** | 0.269*** |
| | (0.056) | (0.043) | (0.042) | | (0.057) | (0.044) |
| **ln(SPILLSIC)** | 0.043 | -0.079*** | | -0.038* | -0.128*** | -0.087*** |
| | (0.026) | (0.023) | | (0.022) | (0.032) | (0.023) |
| **ln(R&D Stock)** | 0.104*** | 0.170*** | 0.167*** | 0.200*** | 0.174*** | 0.120*** |
| | (0.039) | (0.024) | (0.024) | (0.024) | (0.024) | (0.027) |
| **ln(patents)** | 0.420*** | 0.514*** | 0.514*** | 0.514*** | 0.514*** | 0.537*** |
| | (0.02) | (0.014) | (0.014) | (0.014) | (0.014) | (0.015) |
| **Pre-sample FE** | 0.292*** | 0.139*** | 0.136*** | 0.143*** | 0.136*** | 0.152*** |
| | (0.033) | (0.019) | (0.019) | (0.019) | (0.019) | (0.019) |
| | | | | | | **1st Stage F-stat** |
| **ln(SPILLTECH)** | | | | | | 629.2 |
| **ln(SPILLSIC)** | | | | | | 216.7 |
| **Observations** | 9,023 | 21,810 | 21,810 | 21,810 | 21,810 | 14,789 |

**Notes:** Dependent variable is citations-weighted patents. Estimation is conducted using the Negative Binomial model. Standard errors allow for serial correlation through clustering by firm. All columns include time dummies, four digit industry dummies and lagged firm sales. *** p<0.01, ** p<0.05, * p<0.10.

Table 4: Productivity Equation

| | Old Sample | New Sample | | | | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| | **OLS** | **OLS** | **OLS** | **OLS** | **OLS** | **IV** |
| | **Jaffe** | **Jaffe** | **Jaffe** | **Jaffe** | **Mahalanobis** | **Jaffe** |
| **ln(SPILLTECH)** | 0.191*** | 0.236*** | 0.231*** | | 0.269*** | 0.287*** |
| | (0.046) | (0.021) | (0.021) | | (0.026) | (0.027) |
| **ln(SPILLSIC)** | -0.005 | -0.01 | | 0.005 | -0.008 | -0.01 |
| | (0.011) | (0.007) | | (0.007) | (0.01) | (0.011) |
| **ln(Capital)** | 0.154*** | 0.130*** | 0.130*** | 0.132*** | 0.131*** | 0.130*** |
| | (0.012) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| **ln(Employment)** | 0.636*** | 0.693*** | 0.693*** | 0.686*** | 0.694*** | 0.694*** |
| | (0.015) | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| **ln(R&D Stock)** | 0.043*** | 0.015*** | 0.015*** | 0.022*** | 0.016*** | 0.013*** |
| | (0.007) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| | | | | | | **1$^{st}$ Stage F-stat** |
| **ln(SPILLTECH)** | | | | | | 4183.7 |
| **ln(SPILLSIC)** | | | | | | 914.3 |
| **Observations** | 9935 | 27566 | 27566 | 27566 | 27566 | 27390 |

**Notes:** Dependent variable is ln(sales). All columns include firm and year fixed effects and controls for current and lagged industry sales in each firm's output industry. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey-West correction. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 5: R&D Equation

| | Old Sample | New Sample | | | |
|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** |
| | **OLS** | **OLS** | **OLS** | **OLS** | **IV** |
| | **Jaffe** | **Jaffe** | **Jaffe** | **Mahalanobis** | **Jaffe** |
| **ln(SPILLTECH)** | 0.1 | 0.125*** | 0.032* | 0.093** | 0.198*** |
| | (0.076) | (0.034) | (0.019) | (0.04) | (0.046) |
| **ln(SPILLSIC)** | 0.083** | 0.054*** | 0.019* | 0.095*** | 0.050* |
| | (0.034) | (0.017) | (0.01) | (0.021) | (0.026) |
| **ln(R&D/Sales)** | | | 0.670*** | | |
| | | | (0.01) | | |
| | | | | | **1st Stage F-stat** |
| **ln(SPILLTECH)** | | | | | 3362.2 |
| **ln(SPILLSIC)** | | | | | 760.8 |
| **Observations** | 8579 | 28130 | 27794 | 28130 | 25090 |

**Notes:** Dependent variable is ln(R&D/sales). All columns include firm and year fixed effects and controls for current and lagged industry sales in each firm's output industry. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey-West correction. *** p<0.01, ** p<0.05, * p<0.10.

Table 6: Market Value Equation

| | (1) ln(SPILLTEC) | (2) ln(SPILLSIC) | (3) ln(R&D/capital) |
|---|---|---|---|
| **Baseline ($1985 \leq t < 1990$)** | 0.2372*** | -0.0813*** | 0.163*** |
| | (0.044) | (0.014) | (0.01) |
| **$1990 \leq t < 1995$** | 0.015 | 0.005 | -0.012 |
| | (0.017) | (0.009) | (0.011) |
| **$1995 \leq t < 2000$** | 0.115*** | 0.019** | -0.008 |
| | (0.017) | (0.009) | (0.011) |
| **$2000 \leq t < 2005$** | 0.112*** | 0.042*** | -0.023* |
| | (0.02) | (0.01) | (0.012) |
| **$2005 \leq t < 2010$** | 0.014 | 0.006 | -0.044*** |
| | (0.023) | (0.012) | (0.014) |
| **$2010 \leq t \leq 2015$** | -0.014 | -0.014 | -0.061*** |
| | (0.025) | (0.012) | (0.013) |

**Notes:** Dependent variable is ln(Tobin's Q) defined as the market value of equity plus debt, divided by the stock of fixed capital. This table summarizes the results of a single regression. Specifically, it reports the coefficients from allowing the coefficients on ln(SPILLTECH), ln(SPILLSIC), and ln(R&D/Capital) in the specification in column (2) of Table 2 to vary over time. Column (1) reports the estimates for the coefficient on ln(SPILLTECH), which are allowed to vary in each 5-year time frame. Column (2) and (3) report the estimates of the coefficients on ln(SPILLSIC) and ln(R&D/Capital) in each 5-year time period, respectively. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey-West correction. *** p<0.01, ** p<0.05, * p<0.10.

Table 7: Patent Equation

| | (1) ln(SPILLTEC) | (2) ln(SPILLSIC) | (3) ln(R&D/capital) |
|---|---|---|---|
| **Baseline (1985 ≤ t < 1990)** | 0.182*** | -0.075** | 0.161*** |
| | (0.064) | (0.032) | (0.026) |
| **1990 ≤ t < 1995** | 0.067 | 0.065** | -0.032* |
| | (0.059) | (0.032) | (0.019) |
| **1995 ≤ t < 2000** | 0.226*** | -0.032 | -0.02 |
| | (0.077) | (0.032) | (0.02) |
| **2000 ≤ t ≤ 2005** | 0.131* | -0.064* | 0.095*** |
| | (0.077) | (0.035) | (0.022) |

**Notes:** Dependent variable is citations-weighted patents. Estimation is conducted using the Negative Binomial model. This table summarizes the results of a single regression. Specifically, it reports the coefficients from allowing the coefficients on ln(SPILLTECH), ln(SPILLSIC), and ln(R&D stock) in the specification in column (2) of Table 3 to vary over time. Column (1) reports the estimates for the coefficient on ln(SPILLTECH), which are allowed to vary in each t-year time frame. Column (2) and (3) report the estimates of the coefficients on ln(SPILLSIC) and ln(R&D/Capital) in each 5-year time period, respectively. Standard errors allow for serial correlation through clustering by firm. Includes time dummies, four digit industry dummies and lagged firm sales. *** p<0.01, ** p<0.05, * p<0.10.

Table 8: Productivity Equation

| | (1) ln(SPILLTEC) | (2) ln(SPILLSIC) | (3) ln(R&D/capital) |
|---|---|---|---|
| **Baseline (1985 ≤ t < 1990)** | 0.206*** | -0.016** | 0.008* |
| | (0.022) | (0.007) | (0.005) |
| **1990 ≤ t < 1995** | 0.008 | 0.012*** | 0.001 |
| | (0.008) | (0.004) | (0.003) |
| **1995 ≤ t < 2000** | 0.021** | 0.010** | 0.004 |
| | (0.009) | (0.004) | (0.003) |
| **2000 ≤ t < 2005** | -0.006 | 0.019*** | 0.013*** |
| | (0.01) | (0.005) | (0.0003) |
| **2005 ≤ t < 2010** | -0.009 | 0.021*** | 0.010*** |
| | (0.012) | (0.005) | (0.004) |
| **2010 ≤ t ≤ 2015** | -0.01 | 0.014** | 0.009** |
| | (0.004) | (0.006) | (0.004) |

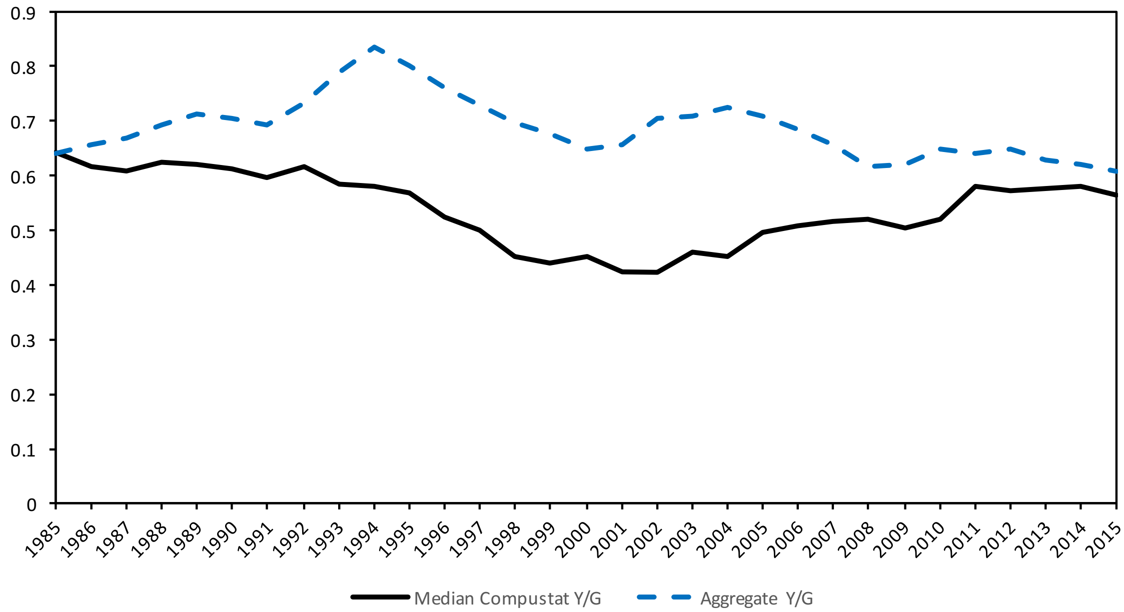
**Notes:** Dependent variable is ln(sales). This table summarizes the results of a single regression. Specifically, it reports the coefficients from allowing the coefficients on ln(SPILLTECH), ln(SPILLSIC), and ln(R&D/Capital) in the specification in column (2) of Table 4 to vary over time. Column (1) reports the estimates for the coefficient on ln(SPILLTECH), which are allowed to vary in each 5-year time frame. Column (2) and (3) report the estimates of the coefficients on ln(SPILLSIC) and ln(R&D stock) in each 5-year time period, respectively. Includes firm and year fixed effects and controls for current and lagged industry sales in each firm's output industry. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey-West correction. *** p<0.01, ** p<0.05, * p<0.10.

Table 9: R&D Equation

| | (1)<br>ln(SPILLTEC) | (2)<br>ln(SPILLSIC) |
|---|---|---|
| **Baseline (1985 ≤ t < 1990)** | 0.138*** | 0.025 |
| | (0.037) | (0.017) |
| **1990 ≤ t < 1995** | -0.028* | 0.003 |
| | (0.015) | (0.008) |
| **1995 ≤ t < 2000** | -0.040** | 0.018** |
| | (0.018) | (0.009) |
| **2000 ≤ t < 2005** | -0.025 | 0.042*** |
| | (-0.018) | (0.009) |
| **2005 ≤ t < 2010** | -0.063*** | 0.058*** |
| | (0.021) | (0.01) |
| **2010 ≤ t ≤ 2015** | -0.097*** | 0.059*** |
| | (0.022) | (0.011) |

**Notes:** Dependent variable is ln(sales). This table summarizes the results of a single regression. Specifically, it reports the coefficients from allowing the coefficients on ln(SPILLTECH), ln(SPILLSIC), and ln(R&D/Capital) in the specification in column (2) of Table 5 to vary over time. Column (1) reports the estimates for the coefficient on ln(SPILLTECH), which are allowed to vary in each 5-year time frame. Column (2) reports the estimates of the coefficients on ln(SPILLSIC) in each 5-year time period. Includes firm and year fixed effects and controls for current and lagged industry sales in each firm's output industry. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey-West correction. *** p<0.01, ** p<0.05, * p<0.10.

Figure 1: Marginal Social Return to R&D




**Notes:** The figure plots the estimated marginal social return to R&D (MSR), which is calculated as $\frac{Y}{G}(\psi_1 + \psi_2)$, where $\frac{Y}{G}$ is the ratio of output to the R&D stock, $\psi_1$ is the elasticity of production with respect to the R&D stock, and $\psi_2$ is the elasticity of production with respect to the technology spillovers. $\psi_2$ and $\psi_2$ are estimated in Table 8. The solid black line uses the median R&D to sales ratio in our sample of Compustat firms as the estimate of $\frac{Y}{G}$. The dotted blue line uses OECD data on total business R&D in the US divided by US GDP as the estimate of $\frac{Y}{G}$. The dotted blue line is normalized to equal the the solid black line in 1985 to highlight changes in the series over time.

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