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Have R&D Spillovers Declined in the 21st Century?*

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Abstract

Slow growth over the last decade has prompted policy attention towards increasing R&D spending, often via the tax system. We examine the impact of R&D on firm performance, both by the firm's own investments and through positive (and negative) spillovers from other firms. We analyse panel data on US firms over the last three decades, and allow for time-varying spillovers in both technology space (knowledge spillover) and product market space (product market rivalry). We show that the magnitude of R&D spillovers remains as large in the second decade of the 21st century as it was in the mid 1980s. Since the ratio of the social return to the private return to R&D is about four to one, this implies that there remains a strong case for public support of R&D. Positive spillovers appeared to temporarily increase in the 1995–2004 digital technology boom. We also show how these micro estimates relate to estimates from the endogenous growth literature and give some suggestions for future work.

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I. Introduction

In the last decade, growth has slowed. In the US, for example, GDP per hour (labour productivity) growth has averaged a scant 1.4 per cent per year since 2005, compared with an average of 2.3 per cent from 1950 through 2004.[1] One way to try to boost growth is to increase research and development (R&D) spending, and a popular policy instrument to deliver this is to lower the cost of R&D through the tax system. Other methods include direct subsidies, increasing the quantity and quality of the supply of research workers, improving the system of intellectual property (IP) protection and a host of other methods. A large literature studies the effects of R&D subsidies and has generally found positive effects.[2]

Implicit in the widespread use of government subsidies are the assumptions that (i) R&D has a positive impact on productivity and (ii) the market will fail to provide the socially optimal level of R&D spending. This paper investigates these twin assumptions and also asks whether these have changed over time. They are crucial in assessing the extent to which policies targeted towards increasing R&D have potential to efficiently mitigate the growth slowdown.

A key question in determining whether market forces deliver too little (or too much) R&D from a social perspective is the magnitude and direction of spillovers. Many theoretical studies have explored the impact of R&D on the interaction among firms and long-run growth.[3] The standard view is that R&D creates knowledge that cannot be fully appropriated by the firm that paid for the investment, and so other firms also benefit without paying the full cost. This partial public good aspect of R&D means that the positive technology spillovers across firms cause the private return to R&D to lie below the social return. The system of IP such as patents is designed to address this, but is highly imperfect in achieving this aim; hence the search for other policy tools such as direct R&D grants or tax credits.

[1]These two figures refer to the average annual percentage change in the US Bureau of Labor Statistics (BLS)'s quarterly series of real output per hour in the non-farm business sector from 2005 through 2018 and from 1950 through 2004, respectively. See https://fred.stlouisfed.org/series/OPHNFB.

[2]See Becker (2015) for a general survey. Microeconomic studies of the effects of R&D tax policies include, for example: Dechezleprêtre et al. (2016) on the effects of UK R&D tax subsidies on R&D investments, patenting and productivity using a regression discontinuity design; Rao (2016) on the effects of the US federal R&D tax credit on R&D spending; and Lucking (2019) on the effects of US state R&D tax credits on employment and productivity growth. Bérubé and Mohnen (2009) and Czarnitzki, Hanel and Rosa (2011) look at the effects of Canadian R&D tax policy on innovation. Studies at the national or industry level include Bloom, Griffith and Van Reenen (2002), Wilson (2009), Corrado et al. (2015) and Chang (2018). Griffith, Sandler and Van Reenen (1995) and Griffith, Redding and Van Reenen (2001) have *ex ante* policy evaluations for the UK of R&D tax credits. Studies looking at direct R&D grants include Bronzini and Iachini (2014) and Bronzini and Piselli (2016) on the effects of R&D subsidies in Italy on R&D spending and patenting.

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

While many empirical studies do support the presence of technology spillovers, there remains a major problem, which is that R&D generates at least two distinct types of spillovers. The first is technology (or knowledge) spillovers, which increase the productivity of other firms that operate in similar technology areas. The second type of spillover is the product market rivalry effect of R&D, where innovations take market share from competing firms. Whereas technology spillovers are beneficial to other firms, R&D by product market rivals has a negative effect on a firm's value through 'business stealing'. Despite a large amount of theoretical research on product market rivalry effects of R&D (including patent race models), there has only been limited econometric work, in large part because it is difficult to distinguish the two types of spillovers. It is important to identify the empirical magnitude of these two types of spillovers. If product market rivalry effects dominate technology spillovers, there may be too much investment in R&D from a social perspective (an 'arms race'), so the conventional wisdom that there is underinvestment in R&D could be overturned. Particular concern has been raised about this in recent decades due to the apparent ease with which large firms can acquire and defend their intellectual property.[4]

One way to address this issue was introduced by Bloom, Schankerman and Van Reenen (2013; hereafter BSV). Their methodology tries to separately identify the two types of spillovers from R&D by measuring the closeness of a pair of firms in technology space compared with product market space. Technology spillovers are identified from the closeness of firms' patenting in similar technological areas, whereas product market rivalry effects are identified from closeness of firms' pattern of sales in the multiple four-digit SIC industries they operate in. The intuition is that R&D by firm A close to firm B in technology is a boon for firm B. But if firm B uses different technologies yet competes in the same product market, a boost in firm A's R&D spending is bad news for firm B. Using data from publicly listed US firms from the early 1980s through 2001, BSV found evidence for both technology spillovers and product market rivalry effects, but argued that the positive R&D spillover effects dominated. In this paper, we apply the approach using an extra 15 years of data (through 2015 except for patents, which end in 2006). We look at four firm outcomes: market value, patenting, productivity and R&D.

We find large positive and statistically significant technology spillovers and smaller negative product market rivalry effects. In contrast to the earlier results, we find somewhat stronger evidence of strategic complementarity in R&D among firms. We use our estimates to conduct a rough welfare analysis which suggests the marginal social return to R&D exceeds the private return to R&D by a substantial amount, about 44 percentage points or a factor of about

[4]For example, Boldrin and Levine (2013).

four.[5] This suggests substantial underinvestment in R&D and an important role for government support. We then show that our estimates of constant technology spillovers can be reconciled with semi-endogenous growth models in which technological innovation is the main driver of economic growth.

We build on a long line of research, perhaps most saliently in the work of Griliches (1992). BSV introduced a method for splitting up the two types of spillovers and many authors have subsequently extended this approach. Manresa (2015) generalises the approach to modelling spillovers in a modified panel data 'pooled' Lasso approach. Lychagin et al. (2016) 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 that 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). We discuss more papers in the literature in Section IX on future work.

The rest of the paper is organised as follows. First, in Section II, we describe the data and measurement of key variables, including the measures of proximity between firms and the R&D tax credit instrumental variable. Next, in Section III, we review the econometric framework and theoretical predictions of the BSV model of firms' value, production, patenting and R&D. We then present the main estimation results in Section IV, before investigating heterogeneity in the coefficients across industries (in Section V) and, most importantly given our motivation, across time periods (in Section VI). Section VII conducts a welfare analysis that allows for time-varying parameters and Section VIII shows how our estimates are consistent with endogenous growth models and, in particular, with recent papers studying the slowdown in R&D productivity. Section IX suggests some directions for future research, before we conclude in Section X.

II. Data

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

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 National Bureau of

[5] We estimate the marginal social return at 58 per cent and the marginal private return at 14 per cent.

Economic Research (NBER) Patent Data Project.[6] The NBER patent data include data from the US Patent and Trademark Office (USPTO) on the universe of utility patents granted between 1976 and 2006 in addition to firm identifiers (gvkey) which allow the matching of 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 that 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 (four-digit SIC), and in many cases a secondary industry code. For lines of business with two codes listed, we allocate 75 per cent of the line's sales to the primary industry and 25 per cent to the secondary industry. We use Compustat Segments data from 1980 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. Third, we draw on the work of Lucking (2019), who extended the database of the tax rules governing state and federal R&D tax credits through 2015.

2. Measuring technological proximity

Technological proximity is measured using the Jaffe (1986) metric as well as the Mahalanobis generalisation 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 $T_i = (T_{i1}, T_{i2}, \ldots, T_{i426})$, where $T_{i\tau}$ is the share of firm i's patents in technology class τ. The Jaffe measure of technological proximity between firm i and firm j is given by

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

Hence, $TECH_{ij}$ is simply the uncentred correlation of firm i's patents and firm j's patents across technology classes. The pool of technology spillovers to firm i in year t, $SPILLTECH_{it}$, is the stock of R&D of all the firms with which firm i interacts in technology space, weighted by the Jaffe measure of technological proximity. Specifically,

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

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

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

3. Measuring product market proximity

Product market proximity is measured using line of business data from the Compustat Segments data set, which provides each firm's sales disaggregated by four-digit industry code. We begin by defining the vector $S_{it} = (S_{i1t}, S_{i2t}, \ldots, S_{i473t})$, 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 the firm's 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 affect 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 period, which likely exacerbates the endogeneity and measurement problems introduced by pooling the data. We therefore use the five previous years of firm sales in order to (a) minimise reverse causality between firm outcomes and product market competition and (b) accurately measure the firm's time-t location in product market space.[7] Product market proximity is measured by the correlation of firms' sales across four-digit industries:

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

Similar to the way in which $TECH_{ij}$ measures the correlation of two firms' patenting across technology classes, SIC_{ij} is the uncentred correlation coefficient for firm i and firm j sales across four-digit industries. The pool of product market spillovers to firm i in year t, $SPILLSIC_{it}$, is then defined as 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.[8] Specifically,

$$(4) \qquad SPILLSIC_{it} = \sum_{j \neq i} SIC_{ij} G_{jt}.$$

[7]The results do not appear sensitive to this choice – using the firm's previous 10 years or 20 years of sales produces similar estimates.

[8]We require sufficient variation in firms' exposure to product market spillovers versus firms' exposure to technology spillovers in order to distinguish between the two types of R&D spillovers. Fortunately, there is substantial independent variation in our measures. The correlation between ln(*SPILLTECH*) and ln(*SPILLSIC*) in our regression sample is 0.4349.

4. Mahalanobis extension

We also construct alternative versions of *SPILLTECH* and *SPILLSIC* using the Mahalanobis distance metric. This measure allows for spillovers between different technology classes in the case of the *SPILLTECH* extension and between different industries in the case of the *SPILLSIC* extension. Spillovers between technology classes and four-digit industries are ruled out by the Jaffe metric (which assumes full spillovers within the same class or industry and nothing otherwise). Complete detail on the definition and construction of the Mahalanobis measures is included in the online appendix. In brief, the Mahalanobis *SPILLTECH* measure quantifies spillovers across technology class by using revealed preference. If two technologies are often located together in the same firm (for example, '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. The Mahalanobis *SPILLSIC* measure is defined analogously for product market spillovers, allowing for spillovers across four-digit industries whereas the Jaffe *SPILLSIC* measure ruled them out. When products within two industries are frequently sold within the same firm, the Mahalanobis *SPILLSIC* measure infers that the distance between these two industries is small.

5. Tax-based instrumental variables

A concern with interpreting the coefficients on the spillover variables as causal is that they might be subject to various endogeneity biases. For example, in the total factor productivity (TFP) equation, there may be an unobserved demand shock for firms operating in a similar technological area that raises their productivity and R&D together. Following Lucking (2019), we combine the effective R&D tax credit rates with state corporate income tax credit rates in order to construct a measure of the cost of R&D in each state. In particular, we model the cost of R&D as the implicit rental rate for R&D capital services, which is given by an extension of the Hall and Jorgenson (1967) user cost formula. We assume a constant interest rate and depreciation rate within each year, so the depreciation rate of R&D and interest rates are absorbed by the year dummies after taking logs. Since we include year fixed effects in all of the empirics, we focus on the log tax component of the user cost, ρ_{st}:

$$\text{(5)} \qquad \ln(\rho_{st}) = \ln\left(\frac{1-(k_{st}+k_t^f)-(\tau_{st}+\tau_t^f)}{1-(\tau_{st}+\tau_t^f)}\right),$$

where k_{st} and k_t^f are the effective state and federal R&D tax credits, and τ_{st} and τ_t^f are the effective state and federal corporate income tax rates. ρ_{st} is defined at the state-by-year level, but there will also be some within state–year variation.[9] Hence, we use ρ_{it} as an instrument for own R&D, G_{it}, $z_{it}^{TECH} = \sum_{j \neq i} TECH_{ij}\rho_{jt}$ as an instrument for $SPILLTECH_{it}$ and $z_{it}^{SIC} = \sum_{j \neq i} SIC_{ij}\rho_{jt}$ as an instrument for $SPILLSIC_{it}$. Note that the tax instruments are firm-specific for three reasons. First, the locations of firms' R&D labs are distributed across different states. We use the location of inventors as revealed in the patent documents to estimate each firm's fraction of R&D activity in each state.[10] Large R&D-performing firms will often have research activity in multiple states. Second, the federal tax system has firm-specific non-linear effects on a firm's tax-adjusted user cost of R&D capital.[11] Third, the instrumental variables for spillovers depend on firm-specific proximity measures ($TECH_{ij}$ and SIC_{ij}).

6. 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 four years of

TABLE 1

Summary statistics

	New sample			Old sample		
	Median	*Mean*	*SD*	*Median*	*Mean*	*SD*
Tobin's Q	1.67	3.30	4.32	1.41	2.36	2.99
Market value	170	2,692	12,496	412	3,913	16,517
R&D stock	31.6	579	2,614	28.7	605	2,722
R&D stock / capital	0.41	0.95	1.64	0.17	0.47	0.91
R&D flow	5.07	95.4	423	4.36	104	469
Technology spillovers	40,670	54,498	48,722	20,091	25,312	19,942
Product market spillovers	15,650	26,822	31,784	2,007	6,494	10,114
Patent flow	1	25.5	129.3	1	16.2	75.0
Citations-weighted patents	10	210	757	4	116	555
Sales	153	2,351	10,041	456	2,879	8,790
Physical capital	36.5	1,021	4,700	122	1,346	4,720
Employment	1,310	12,819	40,431	3,839	18,379	52,826

Note: The means, medians and standard deviations (SDs) are taken over all non-missing observations between 1981 and 2001. The left-hand panel presents summary statistics for the new analysis sample, which contains 1,985 firms. The right-hand panel presents summary statistics for the sample of 705 firms in Bloom, Schankerman and Van Reenen (2013).

[9]This arises from two other sources. First, R&D-performing Compustat firms typically have inventors located in multiple states. We use the location of inventors as detailed on the patents that companies have filed to proxy for the location of these R&D labs and use these as weights for calculating ρ_{it}. Second, the rules of the federal tax code create some non-linearities due to firm history (see Hall (1993) and Rao (2016)). See BSV and Lucking (2019) for more details.

[10]See BSV for details.

[11]See Hall (1993), for example.

data and with large jumps in sales and employment in consecutive years, which may be indicative of mergers and acquisitions (M&A) activity. We exclude the first five years of data (1980–84) 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 the left-hand panel and for the 705 firms in the BSV sample in the right-hand panel. Summary statistics are presented over the period 1981–2001 to facilitate comparison between the two samples. Compared with BSV, the firms in our sample have higher Tobin's Q, are more R&D-intensive (as measured by R&D stock, R&D flow, and stock scaled by physical capital) and 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 matched sample includes many medium and smaller Compustat firms.

III. 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 citations-weighted patenting. Theory has clear predictions for firm market value and knowledge, while the predictions for R&D spending depend on the competitive environment. 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*). Knowledge outputs, which we proxy for using patenting and productivity, should be increasing in the pool of R&D spillovers from technologically similar firms (*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 the size of the pool of spillovers from product market rivals (*SPILLSIC*) in the case of strategic complements and decreasing in the case of strategic substitutes. The relationship between R&D and *SPILLTECH* is ambiguous in either case because it depends on how technology spillovers affect the firm's marginal product of R&D.[12]

1. Market value equation

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

$$\text{(6)} \qquad \ln(Q_{it}) = \gamma_1 \phi \left[\ln\left(\frac{G}{A}\right)_{it-1} \right] + \gamma_2 \ln(SPILLTECH_{it-1}) + \gamma_3 \ln(SPILLSIC_{it-1}) + \gamma_4 X_{it}^V + \eta_i^V + \tau_t^V + \upsilon_{it}^V,$$

[12] See BSV for details.

where Q_{it} is Tobin's Q, $\phi[(\frac{G}{A})_{it-1}]$ 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^V_{it} is a vector of time-varying controls (see notes to tables for details), and η^V_i and τ^V_t are firm and year fixed effects respectively.

2. Patent equation

We estimate a negative binomial of citations-weighted patents:

$$
\begin{aligned}
(7) \qquad P_{it} = \exp\big\{&\lambda_1 \ln(G_{it-1}) + \lambda_2 \ln(SPILLTECH_{it-1}) \\
&+ \lambda_3 \ln(SPILLSIC_{it-1}) + \lambda_4 X^P_{it-1} + \eta^P_i + \tau^P_t + \upsilon^P_{it}\big\},
\end{aligned}
$$

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

3. Productivity equation

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

$$
\begin{aligned}
(8) \qquad \ln(Y_{it}) = &\psi_1 \ln(G_{it-1}) + \psi_2 \ln(SPILLTECH_{it-1}) \\
&+ \psi_3 \ln(SPILLSIC_{it-1}) + \psi_4 X^Y_{it} + \eta^Y_i + \tau^Y_t + \upsilon^Y_{it},
\end{aligned}
$$

where Y_{it} is real sales, X^Y_{it} includes labour and capital, and η^Y_i and τ^Y_t are firm and year fixed effects respectively.

4. R&D equation

R&D factor demand is

$$
\begin{aligned}
(9) \qquad \ln\left(\frac{R}{Y}\right)_{it} = &\alpha_2 \ln(SPILLTECH_{it-1}) + \alpha_3 \ln(SPILLSIC_{it-1}) \\
&+ \alpha_4 X^R_{it} + \eta^R_i + \tau^R_t + \upsilon^R_{it},
\end{aligned}
$$

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

IV. 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.[13] 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, suggesting the importance of simultaneously controlling for both types of spillover. Column 5 uses the Mahalanobis metric to measure the distance between firms in product and technology space. Recall that while the Jaffe measure

TABLE 2

Market value equation

	Old sample	New sample				
	(1) *OLS* *Jaffe*	*(2)* *OLS* *Jaffe*	*(3)* *OLS* *Jaffe*	*(4)* *OLS* *Jaffe*	*(5)* *OLS* *Mahalanobis*	*(6)* *IV* *Jaffe*
ln(*SPILLTECH*)	0.381***	0.324***	0.284***		0.519***	0.102*
	(0.113)	(0.040)	(0.040)		(0.050)	(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*)						3,439.1
ln(*SPILLSIC*)						863.8
Observations	9,944	29,688	29,688	29,688	29,688	26,403

Note: 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 parentheses are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$.

[13] As described above, we approximate ln(R&D/capital) with a sixth-order polynomial in the regressions that are reported in Table 2. The ln(R&D/capital) coefficient reported in the table 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.

TABLE 3

Patent 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*)	0.417***	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***
	(0.020)	(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

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

imposes zero spillovers across different technology classes (industries) for *TECH* (*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 per cent in absolute magnitude. Finally, in column 6, we estimate the market value equation using R&D tax credits to instrument for *SPILLTECH* and *SPILLSIC*. While the relationship between product market spillovers and market value is essentially unchanged compared with 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 lead all firms to increase innovation.

Table 3 displays the estimates of the patent equation. In column 2, we regress citations-weighted patents (using a negative binomial count data model)

TABLE 4

Productivity equation

	Old sample	New sample				
	(1) *OLS* *Jaffe*	*(2)* *OLS* *Jaffe*	*(3)* *OLS* *Jaffe*	*(4)* *OLS* *Jaffe*	*(5)* *OLS* *Mahalanobis*	*(6)* *IV* *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	–0.010		0.005	–0.008	–0.010
	(0.011)	(0.007)		(0.007)	(0.010)	(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)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
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)
						1st stage F-stat
ln(*SPILLTECH*)						4,183.7
ln(*SPILLSIC*)						914.3
Observations	9,935	27,566	27,566	27,566	27,566	27,390

Note: 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 parentheses are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

on our two spillovers measures, the R&D stock, a firm pre-sample fixed effect (FE) which controls for the firm's average citations-weighted patents in the pre-sample period,[14] 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 with 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 *SPILLTECH* 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 most general model, in column 2.

Table 4 summarises the estimates of the production function. Comparing columns 1 and 2, the results on our new sample are similar to the old

[14]See Blundell, Griffith and Van Reenen (1999) for details. The pre-sample period is defined as the five years before the firm enters the regression sample.

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*)	0.100	0.125***	0.032*	0.093**	0.198***
	(0.076)	(0.034)	(0.019)	(0.040)	(0.046)
ln(*SPILLSIC*)	0.083**	0.054***	0.019*	0.095***	0.050*
	(0.034)	(0.017)	(0.010)	(0.021)	(0.026)
ln(R&D/sales)			0.670***		
			(0.010)		
					1st stage F-stat
ln(*SPILLTECH*)					3,362.2
ln(*SPILLSIC*)					760.8
Observations	8,579	28,130	27,794	28,130	25,090

Note: 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 parentheses are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

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 *SPILLSIC* estimated precisely and close to zero. The inputs in production – labour, 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 summarised in Table 5. We find a positive relationship between both types of spillovers and R&D intensity.[15] In our preferred specification, a 10 per cent increase in *SPILLTECH* is associated with a 12.5 per cent increase in R&D intensity, while a 10 per cent increase in *SPILLSIC* is associated with a 5.4 per cent 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

[15]Note that in comparison with the estimates from BSV in column 1, the results on our new sample in column 2 provide stronger evidence of strategic complementarities in R&D among technologically similar firms, because of the statistically significant coefficient on *SPILLTECH*.

rationalised in a model with endogenous patenting decisions. The intuition is that R&D by the firm's competitors reduces the marginal benefit of R&D and thus the firm's propensity to patent.[16]

V. Heterogeneity across sectors

We next explore how our estimates of R&D spillovers vary between manufacturing versus non-manufacturing firms. One difficulty with this exercise is that the vast majority of the firms in our sample are in manufacturing, due to the concentration of R&D and patenting in that sector. Nonetheless we re-estimate equations 6, 7, 8 and 9 allowing the coefficients to vary by industry by interacting each variable with a dummy variable equal to 1 if the firm is a manufacturing firm and 0 otherwise. The results are presented in Table A1 in the online appendix. Almost none of the interaction terms are statistically significant. On the whole, there is little evidence of heterogeneity in the estimated spillovers coefficients for manufacturing versus non-manufacturing firms. Interestingly, the one exception is that there appear to be somewhat larger technology spillovers to productivity in manufacturing. Estimated R&D spillovers from technologically close firms to own firm productivity are 35 per cent higher among manufacturing firms than among non-manufacturing firms, and the difference is statistically significant at the 10 per cent level.[17] This may give some empirical justification to the greater attention policymakers give to manufacturing than to other sectors.

The only other heterogeneity we find evidence of is that the coefficient on capital in the production function is higher in non-manufacturing. BSV looked in more detail at heterogeneity between different high-tech sectors. They found that pharmaceuticals had the largest product market rivalry effects (compared with computer hardware and medical devices), arguably because of the importance of 'me-too' drugs.

VI. Changes over time in the returns to R&D

In this section, we assess how the spillovers estimates have changed over time by allowing the coefficients of interest in equations 6, 7, 8 and 9 to vary over time. This allows us to distinguish between the extent to which changes in the coefficient estimates are due to 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

[16]See appendix A.3 in BSV.

[17]The coefficient on *SPILLTECH* in the productivity equation is 0.147 while the coefficient on *SPILLTECH* interacted with a dummy variable equal to 1 for manufacturing firms is 0.051. 0.051/0.147 = 0.3469.

TABLE 6

Market value equation

	(1) *ln(SPILLTECH)*	*(2)* *ln(SPILLSIC)*	*(3)* *ln(R&D/capital)*
Baseline (1985 ≤ t < 1990)	0.237***	–0.081***	0.163***
	(0.044)	(0.014)	(0.010)
1990 ≤ t < 1995	0.015	0.005	–0.012
	(0.017)	(0.009)	(0.011)
1995 ≤ t < 2000	0.115***	0.019**	–0.008
	(0.017)	(0.009)	(0.011)
2000 ≤ t < 2005	0.112***	0.042***	–0.023*
	(0.020)	(0.010)	(0.012)
2005 ≤ t < 2010	0.014	0.006	–0.044***
	(0.023)	(0.012)	(0.014)
2010 ≤ t ≤ 2015	–0.014	–0.014	–0.061***
	(0.025)	(0.012)	(0.013)

Note: 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 summarises 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 between five-year time frames. Columns 2 and 3 report the estimates of the coefficients on ln(*SPILLSIC*) and ln(R&D/capital) in each five-year period, respectively. Standard errors in parentheses are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Note that the 'baseline' is the linear term (so represents 1985–90) and the interactions are in separate rows, so the marginal effect in any particular year is the sum of the baseline and the relevant interaction (for example, the elasticity between market value and *SPILLTECH* in the 1990–95 period is estimated to be $0.2522 = 0.2372 + 0.0150$).

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 equation 6 and interact dummy variables for each five-year period with the technology spillover variable, the product market spillover variable and firm R&D/capital.[18] Columns 1, 2 and 3 show the time-varying estimates of the coefficient on technology spillovers, product market spillovers and R&D/capital, respectively. Note that the period 1985–89 is the omitted base, so the coefficients in each row are the *additional* effects in each five-year block. For example, in column 1, the elasticity between market value and *SPILLTECH* in the 1990–95 period is estimated to be 0.2522 (= 0.2372+0.015) and the elasticity between market

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

TABLE 7

Patent equation

	(1) *ln(SPILLTECH)*	*(2)* *ln(SPILLSIC)*	*(3)* *ln(R&D stock)*
Baseline ($1985 \leq t < 1990$)	0.182***	–0.075**	0.161***
	(0.064)	(0.032)	(0.026)
$1990 \leq t < 1995$	0.067	0.065**	–0.032*
	(0.059)	(0.032)	(0.019)
$1995 \leq t < 2000$	0.226***	–0.032	–0.020
	(0.077)	(0.032)	(0.020)
$2000 \leq t \leq 2005$	0.131*	–0.064*	0.095***
	(0.077)	(0.035)	(0.022)

Note: Dependent variable is citations-weighted patents. Estimation is conducted using the negative binomial model. This table summarises 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 between five-year time frames. Columns 2 and 3 report the estimates of the coefficients on ln(*SPILLSIC*) and ln(R&D stock) in each five-year period, respectively. Standard errors in parentheses allow for serial correlation through clustering by firm. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Note that the 'baseline' is the linear term (so represents 1985–90) and the interactions are in separate rows, so the marginal effect in any particular year is the sum of the baseline and the relevant interaction.

value and *SPILLSIC* is –0.0763 (= –0.0813+0.005). Looking over Table 6 as a whole, estimated technology spillovers and product market rivalry effects in columns 1 and 2 are quite stable over time, with one notable exception. Positive technology spillovers were 48 per cent larger and negative product market rivalry effects 38 per cent smaller on average during the 10 years encompassing the dot-com boom of 1997–2001.[19] Before and after the dot-com boom, the estimates are very flat and we find no statistically significant changes in the spillovers estimates over time. In contrast to the stable estimates of spillovers, the coefficients on own firm R&D appear to be decreasing over time, especially in the last 15 years of the sample. The coefficient on own R&D is 14 per cent lower in 2000–04 compared with 1985–89, and the difference is significant at the 10 per cent level. In the next five years (from 2005 to 2009) the estimated returns are 27 per cent lower and in the last five years (from 2010 to 2015) they are 37 per cent lower, with both differences again relative to the 1985–89 estimates and significant at the 1 per cent level.

Table 7 allows the coefficients in the patent equation to vary over time. The results in this table also suggest higher knowledge spillovers and lower product market rivalry effects from 1995 to 2004. However, since our patent data set

[19]For technology spillovers: $0.5 \times (0.115 + 0.112) / 0.237 = 0.479$. For product market rivalry: $0.5 \times (0.019 + 0.042) / 0.081 = 0.377$.

TABLE 8

Productivity equation

	(1) ln(SPILLTECH)	(2) ln(SPILLSIC)	(3) ln(R&D stock)
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***
	(0.010)	(0.005)	(0.0003)
2005 ≤ t < 2010	–0.009	0.021***	0.010***
	(0.012)	(0.005)	(0.004)
2010 ≤ t ≤ 2015	–0.010	0.014**	0.009**
	(0.012)	(0.006)	(0.004)

Note: Dependent variable is ln(sales). This table summarises 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 4 to vary over time. Column 1 reports the estimates for the coefficient on ln(*SPILLTECH*), which are allowed to vary between five-year time frames. Columns 2 and 3 report the estimates of the coefficients on ln(*SPILLSIC*) and ln(R&D stock) in each five-year period, respectively. Standard errors in parentheses are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. ***$p < 0.01$, **$p < 0.05$, *$p < 0.10$. Note that the 'baseline' is the linear term (so represents 1985–90) and the interactions are in separate rows, so the marginal effect in any particular year is the sum of the baseline and the relevant interaction.

ends in 2006, 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 a 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 for 1995–99, we find no change in the technology spillovers parameter over time. The estimate of the coefficient on ln(*SPILLSIC*) is also quite stable over time. Except for the first five years of the sample (1985–89), the estimated coefficient on ln(*SPILLSIC*) is always statistically indistinguishable from zero. The own R&D coefficients do not show the same decline as they did for market value – if anything, they are getting larger in later years.

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(*SPILLTECH*) and ln(*SPILLSIC*) do appear to be trending over the past 30 years. In particular, the estimated coefficient on ln(*SPILLTECH*) has

TABLE 9

R&D equation

	(1) ln(SPILLTECH)	(2) ln(SPILLSIC)
Baseline ($1985 \leq t < 1990$)	0.138***	0.025
	(0.037)	(0.017)
$1990 \leq t < 1995$	–0.028*	0.003
	(0.015)	(0.008)
$1995 \leq t < 2000$	–0.040**	0.018**
	(0.018)	(0.009)
$2000 \leq t < 2005$	–0.025	0.042***
	(0.018)	(0.009)
$2005 \leq t < 2010$	–0.063***	0.058***
	(0.021)	(0.010)
$2010 \leq t \leq 2015$	–0.097***	0.059***
	(0.022)	(0.011)

Note: Dependent variable is ln(R&D/sales). This table summarises the results of a single regression. Specifically, it reports the coefficients from allowing the coefficients on ln(*SPILLTECH*) and ln(*SPILLSIC*) 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 between five-year time frames. Column 2 reports the estimates of the coefficients on ln(*SPILLSIC*) in each five-year period. Standard errors in parentheses are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Note that the 'baseline' is the linear term (so represents 1985–90) and the interactions are in separate rows, so the marginal effect in any particular year is the sum of the baseline and the relevant interaction.

decreased over the sample, especially in the past 10 years. Indeed, in the last five years of the sample, we cannot reject the null hypothesis that the coefficient on ln(*SPILLTECH*) is equal to zero. Conversely, the coefficient on ln(*SPILLSIC*) has been trending up over time, suggesting greater strategic complementarity. There is no statistically significant relationship between ln(*SPILLSIC*) and own R&D from 1985 through 1994, while from 1995 through 2015 we do find evidence of positive and increasing strategic complementarity of R&D among product market rivals.

To summarise the results from this section, the estimates of technology and product market spillovers have been reasonably stable for the past 30 years. For 1995–2005, we find greater technology spillovers and smaller negative product market spillovers. This is strongest in the market value equation regressions with ln(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. Finally, we also see increasing strategic complementarities in R&D among product market rivals getting larger over time.

VII. 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,[20] BSV show that we can calculate the marginal private return as

$$(10) \qquad MPR = \frac{Y}{G}(\psi_1 - \sigma_Y \gamma_1),$$

where Y/G is the ratio of output to the R&D stock, σ_Y is the share of the reduction in market value that is due to a decline in output as opposed to a decline in price and is assumed to be one-half, γ_1 is the elasticity of market value with respect to product market rivalry (*SPILLSIC*) and ψ_1 is the elasticity of output with respect to the own R&D stock.

Similarly, the marginal social return can be calculated as

$$(11) \qquad MSR = \frac{Y}{G}(\psi_1 + \psi_2),$$

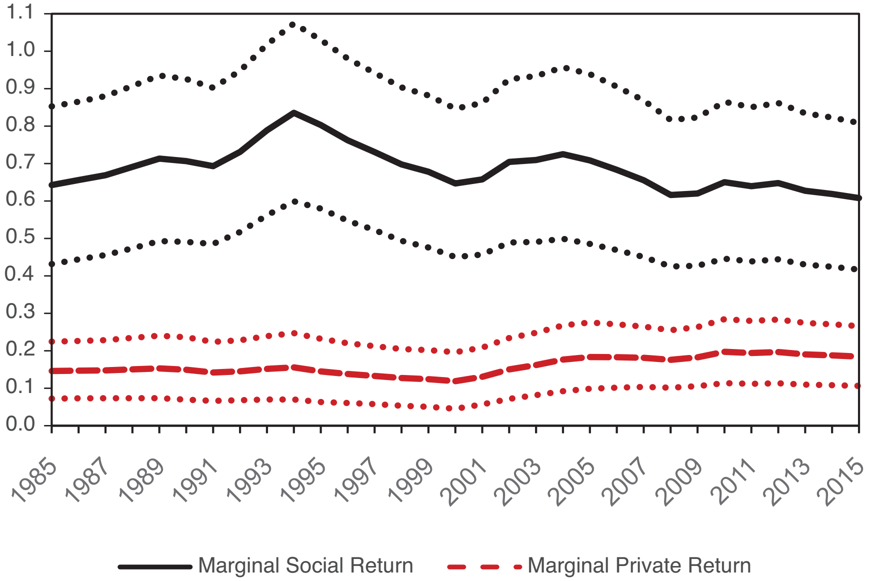
where ψ_2 is the elasticity of output with respect to technology spillovers (*SPILLTECH*). The formula for *MSR* captures the effect of increasing R&D on the firm's own output through ψ_1 and its effect on other firms through ψ_2. Evaluating the marginal social return at the median ratio of output to R&D stock (2.345), $MSR = 2.345 \times (0.015 + 0.231) = 0.577$, or 57.7 per cent. Similarly, the marginal private return evaluated at the median ratio of output to R&D stock is $MPR = 2.345 \times \{0.015 - 0.5 \times (-0.086)\} = 0.136$, or 13.6 per cent. That is, we find that under this simple calculation, the social return to R&D greatly exceeds the private return, by 44.1 percentage points or a ratio of four to one. This implies a substantial underinvestment in R&D from a social perspective.[21]

[20]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.

[21]Compared with the results in BSV, we find a similar marginal social return (57.7 per cent versus 55.0 per cent) and a smaller private return (13.6 per cent versus 20.7 per cent). The smaller private return is due to a smaller output elasticity with respect to R&D capital (ψ_1) as our estimate of the elasticity of market value with respect to product market rivalry (γ_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 ψ_1 is closely offset by the higher estimated output elasticity with respect to technology spillovers (ψ_2).

FIGURE 1

Marginal social and marginal private returns to R&D, evaluated using aggregate data



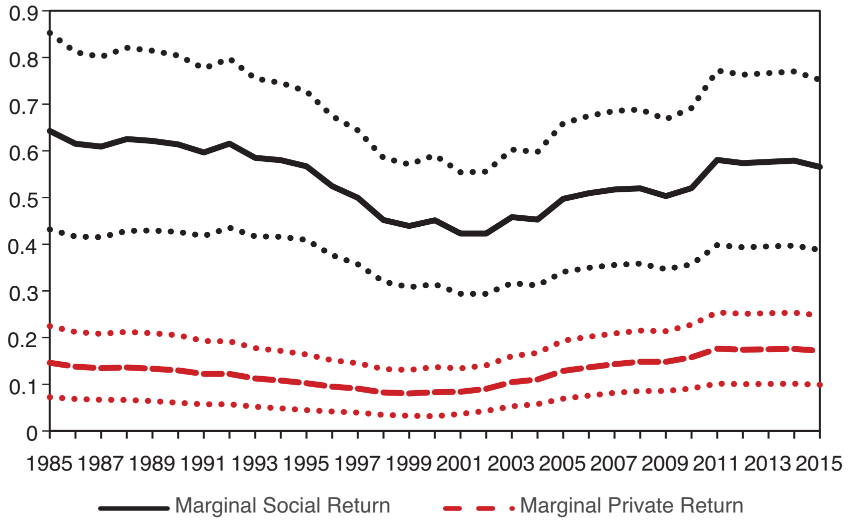
Note: The solid line plots the estimated marginal social return to R&D (MSR), which is calculated as $\frac{Y}{G}(\psi_1 + \psi_2)$, where Y/G is the ratio of output to the R&D stock, ψ_1 is the elasticity of production with respect to the R&D stock and ψ_2 is the elasticity of production with respect to the technology spillovers. The dashed line plots the estimated marginal private return to R&D (MPR), which is calculated as $\frac{Y}{G}(\psi_1 - \sigma_Y \gamma_1)$, where Y/G is the ratio of output to the R&D stock, ψ_1 is the elasticity of production with respect to the R&D stock, γ_1 is the elasticity of market value with respect to product market rivalry and σ_Y is the share of the reduction in market value that is due to a decline in output as opposed to a decline in price. σ_Y is assumed to be one-half, ψ_1 and ψ_2 are estimated in Table 8 and γ_1 is estimated in Table 6. The figure uses OECD data on US GDP divided by total business R&D in the US as the estimate of Y/G. Dotted lines represent 95 per cent confidence intervals.

We can also analyse how the marginal social return and marginal private return to R&D have changed over time using our time-varying estimates of the spillovers coefficients from Tables 6–9. Figure 1 plots the evolution of the MSR and MPR from 1985 through 2015. The solid black line shows the MSR setting *Y*/*G* to GDP divided by the aggregate business R&D stock. The MSR is similar in 2015, at around 0.61, to its value of 0.64 at the beginning of our sample in 1985. In between these years, it rose briefly in the early 1990s but then dipped back to its previous level at the end of the 1990s. The dashed line plots the evolution of the MPR over the same period, again setting *Y*/*G* equal to GDP divided by the aggregate business R&D stock. This measure is relatively flat as well, although it is somewhat larger in 2015, at 0.18, than in 1985, at 0.15. This largely reflects an increase in the MPR during the first half of the 2000s, before and after which the MPR changed little. Overall, there is no strong pattern upwards or downwards for either of the two series and we conclude that both the MSR and the MPR have been broadly stable over this 30-year period.[22]

Note that the MSR is equal to the sum of the production elasticities ψ_1 and ψ_2 divided by the R&D stock as a share of output. Similarly, the MPR is a function of estimated elasticities and the R&D stock as a share of output. In calculating the marginal social return and the marginal private return in Figure 1, we have used the aggregate ratio of US business enterprise R&D (BERD) stock to GDP (from OECD data). We now consider an alternative estimate of the R&D stock as a share of output – namely, the median R&D

FIGURE 2

Marginal social and marginal private returns to R&D, evaluated at Compustat medians



Note: The solid line plots the estimated marginal social return to R&D (MSR), which is calculated as $\frac{Y}{G}(\psi_1 + \psi_2)$, where Y/G is the ratio of output to the R&D stock, ψ_1 is the elasticity of production with respect to the R&D stock and ψ_2 is the elasticity of production with respect to the technology spillovers. The dashed line plots the estimated marginal private return to R&D (MPR), which is calculated as $\frac{Y}{G}(\psi_1 - \sigma_Y\gamma_1)$, where Y/G is the ratio of output to the R&D stock, ψ_1 is the elasticity of production with respect to the R&D stock, γ_1 is the elasticity of market value with respect to product market rivalry and σ_Y is the share of the reduction in market value that is due to a decline in output as opposed to a decline in price. σ_Y is assumed to be one-half, ψ_1 and ψ_2 are estimated in Table 8 and γ_1 is estimated in Table 6. The figure uses the median sales to R&D ratio in our sample of Compustat firms as the estimate of Y/G. Dotted lines represent 95 per cent confidence intervals.

[22]The dotted lines around each series represent bootstrapped 95 per cent confidence intervals.

to sales ratio in our sample of Compustat firms. 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 to output ratio over time may lead us to mischaracterise the evolution of the MSR.[23] Figure 2 plots the evolution of the MSR and MPR from 1985 through 2015 using the median R&D to sales ratio in our sample of Compustat firms as the estimate of the R&D stock to output ratio. The solid black line plots the MSR, which is estimated to be 0.57 in 2015 compared with 0.64 in 1985. This reflects a decline in the MSR during the 1990s and a rise in the following 15 years. The MPR is also largely stable from 1985 to 2015, rising from about 0.15 in 1985 to around 0.17 in 2015. The evolution of the MPR in Figure 2 is similar to the evolution of the MSR – the plot reveals a decline during the 1990s and a subsequent increase during the 2000s and early 2010s. We conclude that using either estimate of the R&D stock to output ratio, the marginal social and marginal private returns to R&D in 2015 are quite similar to their levels 30 years earlier.

VIII. Relationship with endogenous growth models

An interesting question is how our estimates of R&D spillovers relate to those in 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

$$\frac{\dot{A}}{A} = \pi R, \tag{12}$$

where these are economy-wide values. This implies that ideas growth $\dot{A}/A$ is proportional to a measure of research effort R.[24] π 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. Unfortunately, equation 12 is not easily reconcilable with the data as the

[23]There are many differences between the two measures in addition to using the median versus 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 that are not publicly listed. Third, the exact definitions vary, with Compustat based on GAAP accounting regulations and BERD based on the OECD's 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.

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

number of US researchers has increased substantially over time whereas US TFP growth rates have not. Alternatively, semi-endogenous growth models[25] allow for diminishing returns to research productivity ($\beta \geq 0$ in equation 13):

$$(13) \qquad \frac{\dot{A}}{A} = \alpha A^{-\beta} R.$$

The pure endogenous growth model[26] is when $\beta = 0$ so $\pi = \alpha$.[27]

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

$$(14) \qquad Y = A^{\sigma} K^{1-\beta_L} L^{\beta_L}$$

where L is labour, K is capital, β_L is the output elasticity with respect to labour and $0 < \sigma \leq 1$. The marginal social return to the R&D knowledge stock is

$$(15) \qquad \frac{dY}{dA} = \sigma \frac{Y}{A}.$$

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, $\dot{A}$.[28] The change in the ideas stock is then simply

$$(16) \qquad \dot{A} = R,$$

which implies that the growth rate of ideas is

$$(17) \qquad g_A = \frac{\dot{A}}{A} = \frac{R}{A}$$

or

$$(18) \qquad A = \frac{R}{g_A}.$$

[25]For example, Jones (1995) and Kortum (1997).

[26]For example, Romer (1990).

[27]Note that we could change R in equation 13 to R^{λ} 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 about what an appropriate value should be (see Bloom et al. (2017) for a discussion).

[28]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.

Substituting this expression for A back into the formula for *MSR* (equation 15) gives

$$(19) \qquad \frac{dY}{dA} = \sigma \frac{g_A}{(R/Y)}.$$

Equation 19 shows that the MSR is determined by the degree of diminishing returns to the ideas stock (σ), 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 output ratio (R/Y). A more general derivation of equation 19 is in Jones and Williams (1998) – see their equation 16 for example.

Our finding of a broadly stable social return to R&D in the last three decades (see Figures 1 and 2) is consistent with the broad stability of the objects on the right-hand side of equation 19. This conclusion might seem surprising in the light of the evidence in Bloom et al. (2017) that research productivity as measured by π in equation 12 has been *declining* over time. But this evidence is consistent with what we would expect when growth can be described by equation 13 and $\beta \approx 1$, as research productivity, π_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 π. 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)).[29]

IX. Some directions for future research

There are many important future research areas in the realm of R&D spillovers. First, and perhaps most exciting, is explicitly linking R&D spillovers to work coming out of the economics and econometrics of network theory.[30] The technology distance metrics we have implemented for building the R&D network are one example of ways to build up a lattice of potential knowledge 'donors'. But there are many other ways to do this. This raises profound questions of how to causally identify the impact of changes in innovative behaviour in one node of the network on other nodes and also what determines

[29] Jones and Williams (1998) show how the kind of social returns to R&D estimates built from an R&D-augmented Cobb–Douglas production function like equation 8 relate to the formal semi-endogenous growth models reflected in equation 13. In short, a log-linearised approximation of the production function for ideas (equation 13) around the steady-state growth path can be mapped into our estimate of the social rate of return.

[30] For example, Jackson (2010).

how these networks evolve over time. These are generic problems in the area of peer effects and much progress has recently been made.[31]

This discussion leads naturally on to a second class of issues, which is how to empirically measure the relevant dimension of spillovers. We have focused on patent technology class and national product markets. The patent data themselves offer many other options using citations information (the closer we are, the more I cite you), claims information or legal disputes. Customers and supplier chains are another dimension: this could be in goods, services or the technology market. Consider the last aspect, for example. There are many IP transactions to do with selling patents, cross-licensing arrangements, research joint ventures (RJVs) etc. which reveal cross-firm linkages.[32] Some data sets are emerging that do have the details of these technological contracts and these could be used in a more careful way to distinguish whether or not a firm is partially paying for the benefits of another firm's R&D.[33] Another important dimension of spillovers is geographic distance – there is much evidence that people and firms learn more from others who are geographically close, and this is one of the reasons for agglomeration effects.[34] It is straightforward to extend the distance metric approach in this paper to incorporate geography as another proximity dimension alongside technology class and product market.[35] Geographic spillovers are particularly interesting in terms of place-based policies that seek to reinvigorate places that have been 'left behind' over the last few decades – for example, trying to foster growth through universities and technology hubs.[36]

A third avenue for future research is to think more internationally. In this paper, we focus on domestic US spillovers, which is natural as America remains the technological leader in more industries than any other country. It would, however, be fascinating to see to what extent the findings here generalise to other regions such as Europe, Japan or China. Doing so would also raise another question of international spillovers – we should really

[31] For example, Acemoglu, Akcigit and Kerr (2016).

[32] These IP deals are generally unobserved in the standard firm-level data sets such as the Compustat data used in this paper. Technological spillovers are still in principle identified, however. Take our market value equation, for example. If the licensing costs represent the full value derived by firm A from the increase in (technologically close) firm B's R&D, then firm B's R&D will not increase firm A's value (as these will already be incorporated into the market's assessment). Any increase in firm A's value is that *over and above* the financial payments to firm B and thus should be scored as a spillover. Similar arguments hold in production functions when value added (or its equivalent) is the outcome, as these licensing payments are intermediate inputs that are not part of value added. This is not so clear in the patent equation, however, as technological licensing is not directly netted out, but could be controlled for with some accounting variables.

[33] For example, Galasso and Schankerman (2016).

[34] See Moretti (2013).

[35] See Lychagin et al. (2016) for an extensive treatment.

[36] For example, Gruber and Johnson (2019) and Kantor and Whalley (2019).

also be building in more rigorously how firms absorb knowledge from other countries.[37]

Finally, the theoretical basis of empirical studies of spillovers tends to be very simple. A new wave of endogenous growth models taking firm heterogeneity seriously are starting to be developed and structurally estimated on richer data sets than the one we have used here (for example, using census-type data matched to the Business R&D and Innovation Survey (BRDIS)). The advantage of this approach is that the 'deep' parameters can be recovered in principle and used to estimate counterfactuals, welfare and policy simulations.[38] These models are much more demanding, but are clearly an ambitious new frontier in the area of R&D spillovers.

X. Conclusion

Innovation is at the heart of growth, so policies to boost R&D, such as tax credits, could be useful in restoring stronger productivity growth rates in advanced countries. This paper implements a framework to examine the impact of R&D on firm performance. The database is an extension of the one in Bloom, Schankerman and Van Reenen (2013) adding up to an additional 15 years of data. The updated estimates have broad similarity to the original findings but some differences – for example, stronger strategic complementarity of R&D investments. As in the earlier work, we show that there are large positive spillovers among technologically close firms, and negative spillovers from product market rivals due to business-stealing effects. Back-of-the-envelope welfare calculations confirm the earlier paper's findings of a sizeable wedge between the social and private returns to R&D, suggesting $4 of social benefit to every $1 of R&D spent.

The additional data also allow us to explore the changing natures of technology and product market spillovers over time. Perhaps surprisingly, we find that estimated spillovers are reasonably 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 firms. 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 30 years, can be reconciled within the framework of a standard semi-endogenous growth model.

Although the evidence here does suggest that greater public policy support for R&D is justified, it does not tell us exactly what the precise form of policy

[37] Compustat partially does this as the R&D activities are by global multinationals, much of whose activities are outside the US but captured in the consolidated accounts. Furthermore, many of the US stock market listed firms used in Compustat are headquartered outside the US.

[38] For example, Akcigit and Kerr (2018).

intervention should be. One option is through the tax system and, in line with the previous literature, we do find that R&D tax credits are effective in raising firm-level R&D spending. However, tax credits or more direct R&D subsidies through industrial grants may both have a bigger influence on the price of R&D (mainly wages of R&D researchers) than on the volume of R&D if the supply of researchers is inelastic. This motivates policies that may act on the supply side of R&D through increasing the quantity and quality of potential inventors. This may be through increasing the number of students studying science, technology, engineering and maths (STEM subjects) or more radically by increasing the exposure of individuals from low-income families, minorities and women to the chance of becoming a future inventor.[39,40]

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

- Appendix

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[39] See Bell et al. (2019).

[40] We investigate in more detail the trade-offs involved in developing innovation policy based on modern econometric evidence in Bloom, Van Reenen and Williams (2019).

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