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IDENTIFYING TECHNOLOGY SPILLOVERS AND PRODUCT MARKET RIVALRY

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The impact of R&D on growth through spillovers has been a major topic of economic research over the last thirty years. A central problem in the literature is that firm performance is affected by two countervailing "spillovers" : a positive effect from technology (knowledge) spillovers and a negative business stealing effects from product market rivals. We develop a general framework incorporating these two types of spillovers and implement this model using measures of a firm's position in *technology* space and *product market* space. Using panel data on U.S. firms, we show that technology spillovers quantitatively dominate, so that the gross social returns to R&D are at least twice as high as the private returns. We identify the causal effect of R&D spillovers by using changes in federal and state tax incentives for R&D. We also find that smaller firms generate lower social returns to R&D because they operate more in technological niches. Finally, we detail the desirable properties of an ideal spillover measure and how existing approaches, including our new Mahalanobis measure, compare to these criteria.

KEYWORDS: Spillovers, R&D, market value, patents, productivity.

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 R&D on the strategic interaction among firms and long run growth.[2] 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. The second type of spillover is the *product market rivalry effect* of R&D. Whereas technology spillovers are beneficial to other firms, R&D by product market rivals has a negative effect on a firm's value due to business stealing. Despite much theoretical research on product market rivalry effects of R&D (including patent race models), there has been

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[2]See, for example, Spence (1984), Grossman and Helpman (1991), or Aghion and Howitt (1992). Keller (2004) and Jones (2005) have surveys of the literature.

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little 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 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, we need estimates of the impact of product market rivalry to assess whether there is over-investment or under-investment in R&D. To do this, we need to compare social and private rates of return to R&D that appropriately capture both forms of spillovers. If product market rivalry effects dominate technology spillovers, the conventional wisdom that there is (from a welfare perspective) under-investment in R&D could be overturned.

This paper develops a methodology to identify the separate effects of technology and product market spillovers and is based on two main features. First, using a general analytical framework, we develop the implications of technology and product market spillovers for a range of firm performance indicators (market value, citation-weighted patents, productivity, and R&D). The predictions differ across performance indicators, thus providing identification for the technology and product market spillover effects. Second, we empirically distinguish a firm's position in *technology* space and *product market* space using information on the distribution of its patenting across technology fields, and its sales activity across different four-digit industries. This allows us to construct distinct measures of the distance between firms in the technology and product market dimensions.[3] We show that the significant variation in these two dimensions allows us to distinguish empirically between technology and product market spillovers.[4] We also develop a methodology for deriving the social and private rates of return to R&D, measured in terms of the output gains generated by a marginal increase in R&D over heterogeneous firms. These reflect both the positive technology spillovers (for the social return) and negative business stealing effects (for the private return), and thus depend on the position of the firm in both the technology and product market spaces.

Applying this approach to a panel of U.S. firms over the period 1981–2001, we find that both technology and product market spillovers are present and

[3]In an earlier study, Jaffe (1988) assigned firms to technology and product market space, but did not examine the distance between firms in *both* these spaces. In a related paper, Branstetter and Sakakibara (2002) made an important contribution by empirically examining the effects of technology closeness and product market overlap on patenting in Japanese research consortia.

[4]Examples of well-known companies in our sample that illustrate this variation include IBM, Apple, Motorola, and Intel, who are all close in technology space (revealed by their patenting and confirmed by their research joint ventures), but only IBM and Apple competed in the PC market and only Intel and Motorola competed in the semiconductor market, with little product market competition between the two pairs. Appendix D of the Supplemental Material (Bloom, Schankerman, and Van Reenen (2013)) has more details on this and other examples.

quantitatively important, but the technology spillover effects are much larger. As a result, we estimate that the (gross) social rate of return to R&D exceeds the private return, which in our baseline specification are (with some additional assumptions) calculated as 55% and 21%, respectively. At the aggregate level, this implies under-investment in R&D, with the socially optimal level being over twice as high as the level of observed R&D.

A central issue in this paper is empirically distinguishing R&D spillovers from correlated shocks to technology opportunities. If new research opportunities arise exogenously in a given technological area, then all firms in that area will do more R&D and may improve their productivity, an effect that may be erroneously picked up by a spillover measure. This issue is an example of the classic "reflection problem" discussed by Manski (1993). We address this by using changes in the firm-specific tax price of R&D (exploiting changes in federal and state-specific rules) to construct instrumental variables for R&D expenditures, and this allows us, in principle, to estimate the causal impact of R&D spillovers.

We also examine heterogeneity in the effects of spillovers in different industries (computers, pharmaceuticals, and telecommunications) and size classes of firms, finding wide variation in social and private returns to R&D. Technology spillovers are present in all sectors, but smaller firms have significantly lower social returns because they tend to operate in technological "niches" (because few other firms operate in their technology fields, their technology spillovers are more limited). This suggests that policy-makers should reconsider their strong support for higher rates of R&D tax credit for smaller firms, at least on the basis of knowledge spillovers. Of course, there may be other potential justifications for the preferential treatment of smaller firms, such as liquidity constraints.

Our paper has its antecedents in the empirical literature on knowledge spillovers. The dominant approach has been to construct a measure of outside R&D (the "spillover pool") and include this as an extra term in addition to the firm's own R&D in a production, cost, or innovation function. The simplest version is to measure the spillover pool as the stock of knowledge generated by other firms in the industry (e.g., Bernstein and Nadiri (1989)). This assumes that firms only benefit from R&D by other firms in their industry, and that all such firms are treated equally in the construction of the spillover pool. Unfortunately, this makes identification of the strategic rivalry effect of R&D from technology spillovers impossible because industry R&D reflects both influences.[5]

[5]The same is true for papers that use an industry-specific "distance to the frontier" as a proxy for the potential size of the technological spillover. In these models, the frontier is the same for all firms in a given industry (e.g., Acemoglu, Aghion, Lelarge, Van Reenen, and Zilibotti (2007)). Other approaches include using international data and weighting domestic and foreign R&D stocks by measures including imports, exports, and FDI (e.g., Coe, Helpman, and Hoffmaister (2008)).

A more sophisticated approach recognizes that a firm is more likely to benefit from the R&D of other firms that are "close" to it, and models the spillover pool (which we will label "*SPILLTECH*") available to firm i as $SPILLTECH_i = \sum_{j\neq i} w_{ij} G_j$ where w_{ij} is some "knowledge-weighting matrix" applied to the R&D stocks (G_j) of other firms j. All such approaches impose the assumption that the interaction between firms i and j is proportional to the weights (distance measure) w_{ij}. There are many approaches to constructing the knowledge-weighting matrix. The best practice is probably the method first used by Jaffe (1986), exploiting firm-level data on patenting in different technology classes to locate firms in a multidimensional technology space. A weighting matrix is constructed using the uncentered correlation coefficients between the location vectors of different firms. We build on this idea but advance the literature by extending it to the product market dimension by using line of business data for multiproduct firms to construct an analogous distance measure in product market space.[6]

While we use the Jaffe measure of distance as the baseline specification, we also extend the empirical analysis by estimating the model with a number of alternatives. Most importantly, we develop a new Mahalanobis distance measure between firms that exploits the co-location of patenting technology classes within firms. The idea is that firms internally co-locate in technology areas that have the greatest knowledge spillovers, and using the observed co-location of technologies within firms can help to measure technology distances between firms. Using this Mahalanobis distance measure, we estimate even larger spillover effects. In addition, we provide (for the first time) economic microfoundations for the Jaffe measure, and develop a formal, axiomatic comparison of the leading alternative distance measures, based on a set of desirable properties which we argue distance measures should possess.

The paper is organized as follows. Section 2 outlines our analytical framework. Section 3 describes the data and proximity measures and Section 4 discusses the main econometric issues. The core empirical findings are presented in Section 5, with extensions and robustness in Section 6. Section 7 contains the axiomatic approach to measuring closeness, and conclusions are in Section 8. The Supplemental Material (Bloom, Schankerman, and Van Reenen (2013)) contains more details on theory (Appendix A), data (Appendix B), calculation of the distance measures (Appendix C), examples of firm location in product and technology space (Appendix D), endogenizing the choice of technology class (Appendix E), separate econometric analysis of three high tech industries (Appendix F), and the methodology for calculating the social and private rates of return to R&D (Appendix G).

[6]Without this additional variation between firms within industries, the degree of product market closeness is not identified from industry dummies in the cross section. The extent of knowledge spillovers may also be influenced by other factors like geographic proximity (e.g., Jaffe, Trajtenberg, and Henderson (1993)), which we investigate in Section 6.

2. ANALYTICAL FRAMEWORK

We consider the empirical implications of a non-tournament model of R&D with technology spillovers and strategic interaction in the product market.[7] We study a two-stage game. In stage 1, firms decide their R&D spending, and this produces knowledge that is taken as predetermined in the second stage (in the empirical analysis, we will use patents and total factor productivity, TFP, as proxies for knowledge). There may be technology spillovers in this first stage. In stage 2, firms compete in some variable, x (such as price or quantity), conditional on knowledge levels, k. We do not restrict the form of this competition except to assume Nash equilibrium. What matters for the analysis is whether there is strategic substitution or complementarity of the different firms' knowledge in the reduced form profit function. Even in the absence of technology spillovers, product market interaction would create an indirect link between the R&D decisions of firms through the anticipated impact of R&D induced innovation on product market competition in the second stage. There are three firms, labelled 0, τ, and m. Firms 0 and τ interact only in technology space (production of innovations, stage 1) but not in the product market (stage 2); firms 0 and m compete only in the product market.

Although this is a highly stylized model, it makes our key comparative static predictions very clear. Appendix A of the Supplemental Material contains several extensions to the basic model. First, we allow firms to overlap simultaneously in product market and technology space, and also allow for more than three firms. Second, we consider a tournament model of R&D (rather than the non-tournament model which is the focus of this section). Third, we allow patenting to be endogenously chosen by firms rather than only as an indicator of knowledge, k. The main predictions of the model are shown to be robust to all these extensions.[8]

Stage 2. Firm 0's profit function is given by $\pi(x_0, x_m, k_0)$. We assume that the function π is common to all firms. Innovation output k_0 may have a direct effect on profits, as well as an indirect (strategic) effect working through x. For

[7]This approach has some similarities to Jones and Williams (1998, 2000) who examined an endogenous growth model with business stealing, knowledge spillovers, and congestion externalities. Their focus, however, was on the biases of an aggregate regression of productivity on R&D as a measure of technological spillovers. Our method, by contrast, seeks to inform micro estimates through *separately identifying* the business stealing effect of R&D from technological spillovers. Interestingly, despite these methodological differences, we find (like Jones and Williams) that social returns to R&D are about two to four times greater than private returns.

[8]In Section 6.1, we also allow firms to choose their activity across technology fields prior to playing the two-stage game described in this section. In the econometric work, which is based on panel data, we introduce dynamics explicitly in the form of lagged explanatory and dependent variables. Developing a fully dynamic, stochastic model of R&D and growth with both technology and product market spillovers is beyond the scope of this paper. For an example of a theoretical contribution along these lines, see Stokey (1995).

example, if k_0 increases the demand for firm 0 (e.g., product innovation), its profits would increase for any given level of price in the second stage.[9]

The best responses for firms 0 and m are given by $x_0^* = \arg\max_{x_0} \pi(x_0, x_m, k_0)$ and $x_m^* = \arg\max_{x_m} \pi(x_m, x_0, k_m)$, respectively. Solving for second stage Nash decisions yields $x_0^* = f(k_0, k_m)$ and $x_m^* = f(k_m, k_0)$, where $f(\cdot)$ is our generic term for a function. First stage profit for firm 0 is $\Pi(k_0, k_m) = \pi(k_0, x_0^*, x_m^*)$, and similarly for firm m. If there is no strategic interaction in the product market, $\pi(k_0, x_0^*, x_m^*)$ does not vary with x_m, and thus Π^0 does not depend on k_m. We assume that $\Pi(k_0, k_m)$ is increasing in k_0, non-increasing in k_m, and concave.[10]

Stage 1. Firm 0 produces innovations with its own R&D, possibly benefiting from spillovers from firms to which it is close in technology space:

$$k_0 = \phi(r_0, r_\tau), \tag{2.1}$$

where r_0 is the R&D of firm 0, r_τ is the R&D of firm τ, and we assume that the knowledge production function $\phi(\cdot)$ is non-decreasing and concave in both arguments. This means that if there are technology spillovers, they are necessarily positive. We assume that the function $\phi(\cdot)$ is common to all firms. Firm 0 solves the following problem:

$$\max_{r_0} V^0 = \Pi\big(\phi(r_0, r_\tau), k_m\big) - r_0. \tag{2.2}$$

Note that k_m does not involve r_0. The first order condition is $\Pi_1\phi_1 - 1 = 0$, where the subscripts denote partial derivatives with respect to the different arguments. We analyze how exogenous shifts in the R&D of technology and product market rivals (τ and m) affect outcomes for firm 0.[11] Comparative statics yield

$$\frac{\partial r_0^*}{\partial r_\tau} = -\frac{\{\Pi_1\phi_{12} + \Pi_{11}\phi_1\phi_2\}}{H}, \tag{2.3}$$

[9] We assume that innovation by firm m affects firm 0's profits only through x_m. For process innovation, this assumption is certainly plausible. With product innovation, k_m could also have a direct (negative) effect on firm 0's profit. This generalization can easily be introduced without changing the predictions of the model.

[10] The assumption that $\Pi(k_0, k_m)$ is non-increasing in k_m is reasonable unless innovation creates a strong externality through a market expansion effect. In particular, this will hold as long as the products of different firms are 'net' demand substitutes (i.e., when aggregated to the firm level). If competing firms' products were demand complements, then $\Pi(k_0, k_m)$ would be increasing in k_m. Certainly, at $k_m \simeq 0$ this derivative must be negative, as monopoly is more profitable than duopoly. In the empirical work, we find that the value function of a firm is indeed declining in the R&D of its product market competitors.

[11] In the empirical work, we will use instrumental variables to address the potential endogeneity of the R&D of technology and product market rivals.

where $H = \Pi_{11}\phi_1^2 + \Pi_1\phi_{11} < 0$ by the second order conditions. If $\phi_{12} > 0$, firm 0's R&D is positively related to the R&D done by firms in the same technology space, as long as diminishing returns in knowledge production are not "too strong." On the other hand, if $\phi_{12} = 0$ or diminishing returns in knowledge production are strong (i.e., $\Pi_1\phi_{12} < -\Pi_{11}\phi_1\phi_2$), then R&D is negatively related to the R&D done by firms in the same technology space. Consequently, the marginal effect $\frac{\partial r_0^*}{\partial r_\tau}$ is formally ambiguous. In addition,

$$\frac{\partial r_0^*}{\partial r_m} = -\frac{\Pi_{12}\phi_1}{H}, \tag{2.4}$$

where r_m is the R&D of firm m. Thus, firm 0's R&D is an increasing (respectively, decreasing) function of the R&D done by firms in the same product market if $\Pi_{12} > 0$, that is, if k_0 and k_m are strategic complements (respectively, substitutes).[12] We also obtain

$$\frac{\partial k_0}{\partial r_\tau} = \phi_2 \geq 0, \tag{2.5}$$

$$\frac{\partial k_0}{\partial r_m} = 0. \tag{2.6}$$

Finally, let $V^* = \Pi(\phi(r_0^*, r_\tau), k_m) - r_0^*$ denote the optimized value of the firm. Using the above results and the envelope theorem, we obtain

$$\frac{\partial V^*}{\partial r_\tau} = \Pi_1 \frac{\partial k_0}{\partial r_\tau} \geq 0 \quad \text{and} \quad \frac{\partial V^*}{\partial r_m} = \Pi_2 \frac{\partial k_m}{\partial r_m} \leq 0.$$

We now discuss the intuition for the basic predictions of the model, which are summarized in Table I. In the case where there is neither product market rivalry nor technology spillovers, R&D by other firms should have no influence on firm 0's decisions or market value (column (4) in Table I). Now consider the effects of R&D by firms that are close in product market space, without technology spillovers (columns (5) and (6)). First, product market rivals' R&D has a direct, negative influence on firm 0's value, through the business stealing effect. This can operate through two channels—reducing the firm's profit margins or market shares, or both. The reduced form representation of profits, $\Pi(k_0, k_m)$, embeds both channels. Second, R&D by product market rivals

[12]It is worth noting that most models of patent races embed the assumption of strategic complementarity because the outcome of the race depends on the gap in R&D spending by competing firms. This observation applies both to single race models (e.g., Lee and Wilde (1980)) and more recent models of sequential races (e.g., Aghion, Harris, and Vickers (1997)). There are patent race models where this is not the case, but they involve a "discouragement effect" whereby a follower may give up if the R&D gap gets so wide that it does not pay to invest to catch up (Harris and Vickers (1987)).

TABLE I

THEORETICAL PREDICTIONS FOR MARKET VALUE, PATENTS, AND R&D UNDER DIFFERENT ASSUMPTIONS

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
			No Technology Spillovers			Technology Spillovers		
Equation	Comparative Static Prediction	Empirical Counterpart	No Product Market Rivalry	Strategic Complements	Strategic Substitutes	No Product Market Rivalry	Strategic Complements	Strategic Substitutes
Market value	$\partial V_0/\partial r_\tau$	Market value with *SPILLTECH*	Zero	Zero	Zero	Positive	Positive	Positive
Market value	$\partial V_0/\partial r_m$	Market value with *SPILLSIC*	Zero	Negative	Negative	Zero	Negative	Negative
Patents (or productivity)	$\partial k_0/\partial r_\tau$	Patents with *SPILLTECH*	Zero	Zero	Zero	Positive	Positive	Positive
Patents (or productivity)	$\partial k_0/\partial r_m$	Patents with *SPILLSIC*	Zero	Zero	Zero	Zero	Zero	Zero
R&D	$\partial r_0/\partial r_\tau$	R&D with *SPILLTECH*	Zero	Zero	Zero	Ambiguous	Ambiguous	Ambiguous
R&D	$\partial r_0/\partial \mathrm{r}_m$	R&D with *SPILLSIC*	Zero	Positive	Negative	Zero	Positive	Negative

Notes: See text for full derivation of these comparative static predictions. Note that the empirical predictions for the (total factor) productivity equation are identical to the patents equation. Also note that the no technology spillovers case corresponds to $\phi_2 = 0$, and technology spillovers correspond to $\phi_2 > 0$. Strategic complementarity or substitutability between rivals' knowledge stocks is given by the sign of Π_{12}. *SPILLTECH* is the technology-distance weighted sum of all other firms R&D stocks. *SPILLSIC* is the product market-distance weighted sum of all other firms R&D stocks. See text for details.

has no effect on the firm's production of knowledge and thus no direct effect on patenting or TFP (see equation (2.6)). Third, the relationship between the firm's own R&D and the R&D by product market rivals depends on how the latter affects the marginal profitability of the firm's R&D; that is, it depends on the sign of Π_{12} (see equation (2.4)). As expected, R&D reaction functions slope upward if k_0 and k_m are strategic complements and downward if k_0 and k_m are strategic substitutes. The same results for R&D by product market rivals also hold when there are technology spillovers (columns (8) and (9)).

Now suppose there are technology spillovers but no product market rivalry (column (7)). From the knowledge production function (2.1), we see immediately that technology spillovers (r_τ) increase the stock of knowledge (patents), k_0, conditional on the firm's own R&D; that is, spillovers increase the average product of the firm's own R&D. This, in turn, increases the flow profit, $\Pi(k_0, k_m)$, and thus the market value of the firm.[13] At the same time, the increase in k_0 raises the level of total factor productivity of the firm, given its R&D spending. The effect of technology spillovers on the firm's R&D decision, however, is ambiguous because it depends on how such spillovers affect the marginal (not the average) product of its R&D, and this cannot be signed a priori (see equation (2.3)). The same results also hold when there is product market rivalry, regardless of whether it takes the form of strategic complements or substitutes (columns (8) and (9)).

Finally, we note one important caveat regarding the absence of an effect of product market rival R&D on knowledge. Equation (2.6) will only hold if our empirical measure, k, purely reflects knowledge. As we show formally in Appendix A.3 of the Supplemental Material, if patents are costly, then they will be endogenously chosen by a firm, and equation (2.6) will not hold in general, as firms will tend to patent more (less) if knowledge is a strategic complement (substitute).[14] It turns out that there is evidence for this in some of our robustness tests. We also note that, if the measure of total factor productivity is contaminated by imperfect price deflators, product market rival R&D could

[13] In the empirical work, we use a forward looking measure of firm profitability (market value) as our proxy for $V^0 = \Pi(k_0, k_m) - r_0$. Market value should equal the expected present value of the profit stream, which, in our static framework, is simply equal to current profit divided by the interest rate. In the empirical specification, we include year dummies that will capture movements in interest rates as well as other factors.

[14] The intuition is relatively simple. Suppose there is a fixed cost to filing a patent on knowledge. Firms choose to make this investment depending on the benefits of doing so relative to these costs. In equilibrium, with strategic complementarity, when rivals increase R&D spending (thus their stock of knowledge), this increases the marginal profitability of firm 0's R&D. Since we assume that patenting generates a percentage increase in innovation rent ("patent premium"), the profitability of patenting also increases (given the fixed cost of patenting). Thus R&D by product market rivals raises both R&D spending and the patent propensity of firm 0. For empirical evidence of strategic patenting behavior, see Hall and Ziedonis (2001), and Noel and Schankerman (2013).

be negatively correlated with productivity because it will depress firm 0's prices and therefore measured "revenue" productivity.

Three points about identification from Table I should be noted. First, the presence of spillovers can, in principle, be identified from the R&D, patents, productivity, and value equations. Using multiple outcomes thus provides a stronger test than we would have from any single indicator. Second, business stealing is identified only from the value equation. Third, the empirical identification of strategic complementarity or substitution comes only from the R&D equation.[15]

3. MEASURES OF PROXIMITY AND DATA

In this section, we develop some theoretical foundations for the technology proximity measure, and then briefly describe the construction of our data set and how we move from the discrete indicator of proximity in the theory section to a continuous empirical metric. Appendix B of the Supplemental Material provides details on the data, with the data and estimation files to replicate all results available online (Bloom, Schankerman, and Van Reenen (2013)).

3.1. *Modeling Technological Proximity Measures*

Technological proximity measures are rarely given a clear microeconomic foundation or statistical justification. In Section 7, we consider more formally the desirable properties of spillover measures. In this section, we provide some microfoundations for the well-known Jaffe (1986) measure of spillovers and our Mahalanobis generalization of it. The basic idea is that knowledge is transferred between firms when the scientists are "exposed" to each other. With each encounter, a knowledge transfer occurs with a probability that depends on the proximity of the (possibly different) fields in which the scientists work. The expected knowledge spillover from one firm to another is the aggregation of these transfers.[16]

To formalize, consider an economy with J firms. Each firm $i \in (1, J)$ has a fixed number of scientists, n_i which is equivalent to the R&D effort (r) discussed in the previous section. These scientists are allocated across $\tau \in (1, Y)$ technology classes (or "fields"), and we take this allocation as the exogenous

[15] Identification cannot be obtained from the knowledge (patents and productivity) or value equations because the predictions are the same for both forms of strategic rivalry.

[16] A related approach has been developed in the sociology literature to measure ethnic segregation. Lieberson (1981) proposed a measure of ethnic segregation based on the probability that a randomly drawn member of one ethnic group would encounter a member of another group. For discussion of alternative measures of segregation, see Massey and Denton (1986), and White (1986). For recent empirical work applying these measures to residential segregation and ideological segregation in media, see Cutler, Glaeser, and Vigdor (1999), and Gentzkow and Shapiro (2010), respectively.

technological profile of the firm (we consider the endogenous allocation of R&D efforts across fields in Section 6.1 below). Let $n_{i\tau}$ denote the number of scientists from firm i in field τ, and $n = \sum_{i=1}^{J} n_i$ denote the total number of scientists in the economy (where $n_i = \sum_{\tau=1}^{Y} n_{i\tau}$). We assume that when a scientist in technology field τ from firm i is exposed to a scientist from firm j in field q, a unit of knowledge is transferred with probability $\omega_{\tau q}$. To begin, we make three assumptions: (i) knowledge transfer occurs only within a given field, not across fields (we allow for cross-field spillovers later); (ii) the probability of transfer does not depend on the identity of the scientists involved, and (iii) the probability of a transfer is the same for each field. To summarize: $\omega_{\tau q} = \omega$ for $\tau = q$ and $\omega_{\tau q} = 0$ for $\tau \neq q$. Note that learning from an encounter between scientists from firms i and j occurs symmetrically. An "encounter" could be face to face, such as in a conference or coffee shop, or it could be virtual, such as exchanging scientific publications online. The physical encounter interpretation is pursued when we examine geographic spillovers in Section 6.2.

The expected number of encounters between scientists of firms i and j in technology field τ is $n_{i\tau} n_{j\tau}$, and the expected knowledge transferred in field τ is $\omega n_{i\tau} n_{j\tau}$. The expected knowledge transferred to firm i from firm j is therefore

$$(3.1) \qquad SPILLTECH_{ij} = \omega \sum_{\tau=1}^{Y} n_{i\tau} n_{j\tau} = \omega \sum_{\tau=1}^{Y} \left(\frac{n_{i\tau}}{n_i} \frac{n_{j\tau}}{n_j} \right) n_i n_j.$$

Define the $1 \times Y$ vector $F_i = (F_{i1}, \ldots, F_{iY})$, where $F_{i\tau} = \frac{n_{i\tau}}{n_i}$ and similarly for $F_j = (F_{j1}, \ldots, F_{jY})$. We define the "exposure" measure of technological proximity between two firms as $TECH^{\mathrm{E}}_{ij} = F_i F'_j n_i$ and the technology spillover "pool" for firm i as

$$(3.2) \qquad SPILLTECH^{\mathrm{E}}_{i} = \omega \sum_{j \neq i} TECH^{\mathrm{E}}_{ij} n_j.$$

The spillover pool is the weighted sum of the number of scientists of other firms, where the weights are the "exposure" measure of proximity. The exposure measure is closely related to the Jaffe measure of proximity. The term $F_i F'_j$ is the uncentered covariance between the distributions of scientists across technology fields. We call this the Jaffe covariance index, $TECH^{\text{J-COV}}_{ij}$, and define the corresponding spillover measure $SPILLTECH^{\text{J-COV}}_{i} = \omega \sum_{j \neq i} TECH^{\text{J-COV}}_{ij} n_j$. Note that $TECH^{\mathrm{E}}_{ij} = n_i TECH^{\text{J-COV}}_{ij}$ so $SPILLTECH^{\mathrm{E}}_{i} = n_i SPILLTECH^{\text{J-COV}}_{i}$. Since the generic empirical relationships we will estimate in Section 4 take the log-linear form, estimation using the exposure and Jaffe covariance measures will be empirically equivalent.

The traditional Jaffe (1986) measure of closeness, $TECH^{\mathrm{J}}_{ij} = \frac{F_i F'_j}{(F_i F'_i)^{1/2} (F_j F'_j)^{1/2}}$, normalizes the uncentered covariance in $TECH^{\text{J-COV}}_{ij}$ on the standard deviation of the share vectors. This has the attractive empirical feature that the closeness measure will not automatically rise when technological fields are aggregated; that is, F_iF_i' will increase, but so will $(F_iF_i')^{1/2}(F_jF_j')^{1/2}$. Thus, the traditional Jaffe measure is more robust to aggregation across fields (e.g., moving from five digit classes to four digit classes) than the simple exposure based measures. Appendix C.1 of the Supplemental Material discusses this in detail. For both this reason and in order to be consistent with the existing literature, we use the traditional Jaffe measures in our baseline results. However, in Section 7, we discuss the properties of many different measures of proximity in relation to some ex ante desirable features of proximity indices. We also show the robustness of our results to many alternative distance metrics in Section 6.3.

3.2. *Mahalanobis Extension*

The exposure measure treats technology areas as orthogonal to each other in the sense that knowledge is transferred only if scientists from different firms "meet" in the same technology field. There are two reasons this is incomplete. First, there is likely to be genuine knowledge complementarity across technology areas, especially in modern high-tech innovation (e.g., biomedical engineering). Second, from a measurement perspective, the plausibility of the assumption that knowledge transfers do not occur across technology areas obviously depends on the level of aggregation of fields. For example, if patent office examiners sometimes erroneously allocate patents in the class "arithmetic processing calculating" to "processing architectures and instruction processing," then we would like a distance metric to recognize these as closer together (the Mahalanobis measure below does exactly this). In this subsection, we generalize the analysis to allow for spillovers across technology fields.

Assume that $\omega_{\tau q} \geq 0$ for all τ, q. Let $\Omega = [\omega_{\tau q}]$ denote the $\Upsilon \times \Upsilon$ matrix that describes the probability of knowledge transfer when two scientists from technology fields τ and q meet.[17] In this generalized setup, knowledge transfer occurs as long as $\omega_{\tau q} > 0$. Following the earlier argument, the expected knowledge spillover between firm i and j is given by

$$SPILLTECH_{ij} = \sum_{\tau=1}^{\Upsilon}\sum_{q=1}^{\Upsilon} \omega_{\tau q} n_{i\tau} n_{jq} = \sum_{\tau=1}^{\Upsilon}\sum_{q=1}^{\Upsilon} \omega_{\tau q}\left(\frac{n_{i\tau}}{n_{i\cdot}}\frac{n_{jq}}{n_{j\cdot}}\right) n_{i\cdot} n_{j\cdot}. \tag{3.3}$$

[17]In the empirical implementation, the elements of Ω are based on the extent of co-location of patenting across technology fields.

Using the vectors $F_i = (\frac{n_{i1}}{n_{i\cdot}}, \dots, \frac{n_{i\Upsilon}}{n_{i\cdot}})$ and $F_j = (\frac{n_{j1}}{n_{j\cdot}}, \dots, \frac{n_{j\Upsilon}}{n_{j\cdot}})$, we can write the Mahalanobis generalization of the exposure measure of proximity, $TECH_{ij}^{\mathrm{EM}}$, as $TECH_{ij}^{\mathrm{EM}} = F_i \Omega F_j' n_{i\cdot}$. Then the spillover pool for firm i is given by

$$(3.4) \qquad SPILLTECH_i^{\mathrm{EM}} = \sum_{j \neq i} TECH_{ij}^{\mathrm{EM}} n_{j\cdot} = \sum_{j \neq i} F_i \Omega F_j' n_{i\cdot} n_{j\cdot}.$$

3.3. *Extension to Product Market Proximity*

With suitable reinterpretation, the preceding microfoundations for technological proximity measures can also be applied to measures of product market closeness. The basic idea is that each "encounter" between two firms in a product market generates a (probabilistic) leakage of information that can be used by one firm to compete more effectively with the other (inducing the product market rivalry effect discussed in the theoretical model in Section 1). In this case, we reinterpret the n_{iq} as the number of sales agents, which we proxy by sales from firm i in product market q. To keep the notation distinct, we use a "tilde" to denote variables for product market closeness, for example, $\tilde{n}_{iq}$ rather than n_{iq}. We define the vector $\tilde{F}_i = (\tilde{F}_{i1}, \dots, \tilde{F}_{i\Upsilon})$, where $\tilde{F}_{i\tau} = \frac{\tilde{n}_{i\tau}}{\tilde{n}_i}$, as the distribution of firm i's sales across the different product markets in which it operates. Following the same argument as before, we obtain the exposure measure of product market proximity between firms i and j, $SIC_{ij}^{\mathrm{E}} = \tilde{F}_i \tilde{F}_j' \tilde{n}_i$, and the product market spillover "pool" for firm i:

$$(3.5) \qquad SPILLSIC_i^{\mathrm{E}} = \tilde{\omega} \sum_{j \neq i} SIC_{ij}^{\mathrm{E}} \tilde{n}_j.$$

As before, we can also derive a Mahalanobis version of the product market proximity and spillover measures. Since this is trivial, we skip that derivation for brevity. However, it is worth reiterating that, as with the technology measure, the exposure measure of product market closeness treats product markets as orthogonal to each other. This is unrealistic because product market information in one area is likely to benefit firms in other, related product markets.[18] In addition, the plausibility of the assumption that product market knowledge transfers do not occur across product market fields obviously depends on the level of aggregation of these fields. For both reasons, the Mahalanobis generalization is also important for the product market measures of proximity and spillovers.

[18]This is especially relevant when these areas represent demand substitutes (as we assume in the theory in Section 1), since product market rivalry generates profit erosion only if the products in question are substitutes.

3.4. *Compustat and Patents Data*

We use firm level accounting data (sales, employment, capital, etc.) and market value data from U.S. Compustat 1980–2001 and match this into the U.S. Patent and Trademark Office (USPTO) data from the NBER data archive (see Hall, Jaffe, and Trajtenberg (2001)). These contain detailed information on almost three million U.S. patents granted between January 1963 and December 1999, and all citations made to these patents between 1975 and 1999 (Jaffe and Trajtenberg (2002)). Since our method requires information on patenting, we kept all firms who patented at least once since 1963 (i.e., firms that had no patents at all in the 37-year period were dropped), leaving an unbalanced panel of 715 firms with at least four observations between 1980 and 2001. Since patents can be very heterogeneous in value, our main results weight patents counts by their future citations, so the dependent variable is "citation-weighted patent counts."[19]

The book value of capital is the net stock of property, plant, and equipment, and employment is the number of employees. R&D is used to create R&D capital stocks calculated using a perpetual inventory method with a 15% depreciation rate (following inter alia Hall, Jaffe, and Trajtenberg (2005)). So the R&D stock, G, in year t is $G_t = R_t + (1-\delta)G_{t-1}$, where R is the R&D flow expenditure in year t and $\delta = 0.15$. We use deflated sales as our output measure, but also compare this with value added specifications. Industry price deflators were taken from Bartelsman, Becker, and Gray (2000) until 1996 and then the BEA four digit NAICS Shipment Price Deflators thereafter. For Tobin's Q, firm value is the sum of the values of common stock, preferred stock, and total debt net of current assets. The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries, and intangibles other than R&D.

3.5. *Calculating Technological Proximity*

The technology market information is provided by the allocation of all patents by the USPTO into 426 different technology classes. We use the average share of patents per firm in each technology class over the period 1970 to 1999 as our measure of technological activity, defining the vector $T_i = (T_{i1}, T_{i2}, \ldots, T_{i426})$, where $T_{i\tau}$ is the share of patents of firm i in technology class τ. T_i is the empirical counterpart to F_i in Section 3.1. As noted above, our

[19]Since later cohorts of patents are less likely to be cited than earlier cohorts, it is important that we control for time dummies. We also show that all the results are robust to using simple counts of patents (see Bloom, Schankerman, and Van Reenen (2007)). Finally, the results are robust to more sophisticated normalizations of the patent citations assuming some parametric form for the citation distribution function (e.g., Hall, Jaffe, and Trajtenberg (2005)).

basic technology closeness measure is calculated as the uncentered correlation between all firm i, j pairings, following Jaffe (1986):

$$(3.6)\qquad TECH_{ij} = \frac{(T_i T_j')}{(T_i T_i')^{1/2}(T_j T_j')^{1/2}}.$$

For notational simplicity, in what follows, we simply denote this as $TECH_{ij}$ (rather than $TECH_{ij}^{J}$). This index ranges between zero and 1, depending on the degree of overlap in technology, and is symmetric to firm ordering, so that $TECH_{ij} = TECH_{ji}$.[20] We construct the pool of technology spillover R&D for firm i in year t, $SPILLTECH_{it}$, as

$$(3.7)\qquad SPILLTECH_{it} = \sum_{j\neq i} TECH_{ij} G_{jt},$$

where G_{jt} is the stock of R&D. The stock of R&D is our empirical analog to the number of scientists, n_j, discussed in Section 3.1.

3.6. *Calculating Product Market Proximity*

Our main measure of product market closeness uses the Compustat Segment Dataset on each firm's sales, broken down into four digit industry codes (lines of business). On average, each firm reports sales in 5.2 different four digit industries, spanning 597 industries across the sample. We use the average share of sales per industry within each firm as our measure of activity by product market, defining the vector $S_i = (S_{i1}, S_{i2}, \dots, S_{i597})$, where S_{ik} is the share of sales of firm i in the four digit industry k.[21] S_i is the empirical counterpart to $\widetilde{F}_i$ in Section 3.1. The product market closeness measure for any two different firms i and j, SIC_{ij}, is then calculated as the uncentered correlation between all firms pairings in an exactly analogous way to the technology closeness measure:

$$(3.8)\qquad SIC_{ij} = \frac{(S_i S_j')}{(S_i S_i')^{1/2}(S_j S_j')^{1/2}}.$$

[20]The main results pool the patent data across the entire sample period, but we also experimented with subsamples. Using just a pre-sample period (e.g., 1970–1980) reduces the risk of endogeneity, but increases the measurement error due to timing mismatch if firms exogenously switch technology areas. Using a period more closely matched to the data has the opposite problem (i.e., greater risk of endogeneity bias). In the event, the results were reasonably similar since firms only shift technology area slowly. Using the larger 1963–2001 sample enabled us to pin down the firm's position more accurately, so we kept to this as the baseline assumption.

[21]The breakdown by four digit industry code was unavailable prior to 1993, so we pool data 1993–2001. This is a shorter period than for the patent data, but we perform several experiments with different assumptions over timing of the patent technology distance measure to demonstrate robustness (see below).

We construct the pool of product market R&D for firm i in year t, $SPILLSIC_{it}$, as

$$SPILLSIC_{it} = \sum_{j \neq i} SIC_{ij} G_{jt}. \tag{3.9}$$

To control for industry demand shocks, we use a lagged firm-specific measure of industry sales that is constructed in the same way as the *SPILLSIC* variable. We use the same distance weighting technique, but instead of using other firms' R&D stocks, we used rivals' sales. This is to mitigate the risk that *SPILLSIC* simply reflects industry demand shocks.

3.7. *The Mahalanobis Distance Metric*

One drawback of the Jaffe (1986) distance metric in equations (3.6) and (3.8) is that it assumes that spillovers only occur within the same technology class, but rules out spillovers between different classes. We addressed this concern in the previous discussion of microfoundations to proximity measures, where we developed a (Mahalanobis) extension to the Exposure and Jaffe measures. The empirical implementation of this theoretical metric exploits the Mahalanobis norm to identify the distance between different technology classes based on the frequency with which patents are taken out in different classes by the same firm (which we refer to as co-location). The calculation of this Mahalanobis measure of spillovers, $SPILLTECH^{\mathrm{M}}$, is notationally quite involved, so it presented in Appendix C.2 of the Supplemental Material. A similar distance measure can also be constructed for the distance between firms in product market space, which we call $SPILLSIC^{\mathrm{M}}$. We present results based on both the Jaffe and Mahalanobis distance metrics in the empirical section.

3.8. *Some Issues With the Data Set*

Although the Compustat/NBER database is the best publicly available data set to implement our framework, there are issues with using it. First, the finance literature has debated the extent to which the breakdown of firm sales into four digit industries from the Compustat Segment Data Set is reliable.[22] We examine this problem using BVD, an alternative firm-level database to calculate product market closeness, in Section 6.3.2. Second, Thompson and Fox-Kean (2005) have argued that the three digit patent classification may be too coarse, so we examine the more disaggregated patent subclass data they used in

[22] For example, Villalonga (2004) argued that firms engage in strategic reporting to reduce their diversification discount. It should be noted that this is a far greater problem in the service sector due to the difficulties in classifying service sector activity, and Villalonga (2004) in fact found no discount in manufacturing. Since our sample is manufacturing focused (81% of our R&D is in manufacturing), this issue is less problematic here.

Section 6.3.3. Third, Compustat only contains firms listed on the stock market, so it excludes smaller firms, but this is inevitable if one is going to use market value data. Nevertheless, R&D is concentrated in publicly listed firms, and our data set covers the bulk of reported R&D in the U.S. economy. Further, we do not drop firms that exit, enter or those that only operate in one line of business. Sample selection issues are discussed in more detail in Appendix B.4 of the Supplemental Material.

3.9. *Descriptive Statistics of SPILLTECH and SPILLSIC*

To distinguish between the effects of technology spillovers and product market rivalry, we need variation in the distance metrics in technology and product market space. To gauge this, we do several things. First, we calculate the raw correlation between the measures *SIC* and *TECH*, which is 0.469. Further, after weighting with R&D stocks following equations (3.7) and (3.9), the correlation between $\ln(\mathit{SPILLTECH})$ and $\ln(\mathit{SPILLSIC})$ is 0.422. For estimation in logarithms with fixed effects and time dummies, the relevant correlation in the change of $\ln(\mathit{SPILLTECH})$ and $\ln(\mathit{SPILLSIC})$ is only 0.319. Although these correlations are all positive and significant at the 1% level, they are well below unity, implying substantial independent variation in the two measures. Second, we plot the distance measure *SIC* against *TECH* in Figure 1, from which it is apparent that the positive correlation we observe is caused by a dispersion

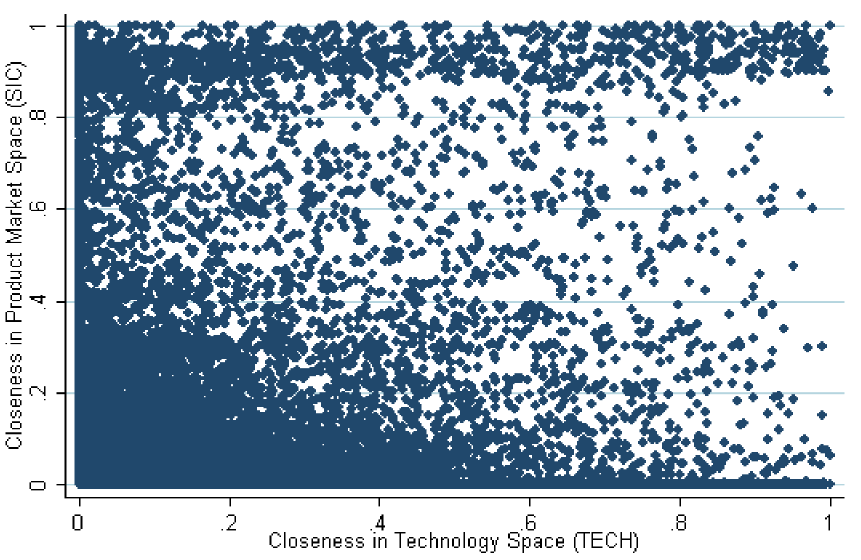

FIGURE 1.—*SIC* and *TECH* correlations. *Notes*: This figure plots the pairwise values of *SIC* (closeness in product market space between two firms) and *TECH* (closeness in technology space) for all pairs of firms in our sample.

TABLE II

DESCRIPTIVE STATISTICS

Variable	Mnemonic	Median	Mean	Standard Deviation
Tobin's Q	V/A	1.41	2.36	2.99
Market value	V	412	3,913	16,517
R&D stock	G	28.7	605	2,722
R&D stock/fixed capital	G/A	0.17	0.47	0.91
R&D flow	R	4.36	104	469
Technological spillovers	*SPILLTECH*	20,091	25,312	19,942
Product market rivalry	*SPILLSIC*	2,007	6,494	10,114
Patent flow		1	16.2	75
Cite-weighted patents	P	4	116	555
Sales	Y	456	2,879	8,790
R&D-weighted sales/R&D stock	Y/G	2.48	3.83	19.475
Fixed capital	A	122	1,346	4,720
Employment	N	3,839	18,379	52,826

Notes: The means, medians, and standard deviations are taken over all non-missing observations between 1981 and 2001; values measured in 1996 prices in $million.

across the unit box rather than a few outliers. Finally, in Appendix D of the Supplemental Material, we discuss examples of well-known firms that are close in technology but distant in product market space, and close in product market but distant in technology space. For example, in our sample period, IBM was technologically close to Intel, Motorola, and Apple (*TECH* correlations of 0.76, 0.46, and 0.64, respectively, compared to the sample average of 0.038), as the technologies IBM uses for computer hardware are closely related to those used by these other companies. However, while IBM is close to Apple in product market space (*SIC* correlation of 0.65, compared to the sample average of 0.015), due to their direct competition in personal computers, IBM is not close to Intel and Motorola (*SIC* correlations of 0.01), reflecting the fact that they produce semiconductor chips, not computer hardware, and IBM produces relatively few (high end) semiconductor chips.

Table II provides some basic descriptive statistics. The firms in our sample are large (median employment is 3,839), but with much heterogeneity in size, R&D intensity, patenting activity, and market valuation. The two spillover measures also differ widely across firms.

4. ECONOMETRICS

In the theory discussion summarized in Table I, there are three key endogenous outcome variables. Two of these (market value and R&D expenditure) are directly observable, while the third (knowledge) can be proxied by both citation-weighted patents and also total factor productivity, generating four empirical measures.[23] We first discuss generic issues of identification with all four measures, and then turn to specific problems with each.

4.1. *Identification*

We are interested in investigating the generic relationship:

$$\ln Q_{it} = \beta_1 \ln G_{it} + \beta_2 \ln SPILLTECH_{it} + \beta_3 \ln SPILLSIC_{it} + \beta_4 X_{it} + u_{it}, \tag{4.1}$$

where the outcome variable(s) for firm i at time t is Q_{it}, the main variables of interest are *SPILLTECH* and *SPILLSIC*, X_{it} is a vector of controls, and the error term is u_{it}. There are three issues to address in estimating equation (4.1): unobserved heterogeneity, endogeneity, and dynamics.

First, to deal with unobserved heterogeneity, we will assume that the error term is composed of a correlated firm fixed effect (η_i), a full set of time dummies (τ_t), and an idiosyncratic component (υ_{it}) that we allow to be heteroskedastic and serially correlated. In all regressions, we will control for fixed effects by including a full set of firm-specific dummies, except for the patents equation where the nonlinear count process requires a special treatment explained below. The time dimension of the company panel is relatively long, so the "within groups bias" on weakly exogenous variables (see Nickell (1981)) is likely to be small.[24]

Second, we have the issue of endogeneity due to transitory shocks. To construct instruments, we exploit supply side shocks from tax-induced changes to the user cost of R&D capital. Details are in Appendix B.3 of the Supplemental Material, but we sketch the strategy here. The Hall–Jorgenson user cost of capital for firm i, ρ_{it}^{U}, is

$$\rho_{it}^{\mathrm{U}} = \frac{(1 - D_{it})}{(1 - \tau_{st})}\left[I_t + \delta - \frac{\Delta p_t}{p_{t-1}}\right], \tag{4.2}$$

where D_{it} is the discounted value of tax credits and depreciation allowances, τ_{st} (shorthand for $\tau_{s_i t}$) is the rate of corporation tax (which has a state as well as a federal component), I_t is the real interest rate, δ is the depreciation rate of R&D capital, and $\frac{\Delta p_t}{p_{t-1}}$ is the growth of the R&D asset price. Since $[I_t + \delta - \frac{\Delta p_t}{p_{t-1}}]$ does not vary between firms, we focus on the tax price component of the user cost, $\rho_{it}^{\mathrm{P}} = \frac{(1-D_{it})}{(1-\tau_{st})}$.

Values of ρ_{it}^{P} of unity are equivalent to R&D tax neutrality, while values below unity denote net tax incentives for R&D. ρ_{it}^{P} will vary across firms for

[23]For an example of this multiple equation approach to identify the determination of technological change, see Griliches, Hall, and Pakes (1991).

[24]In the R&D equation, for example, the mean number of observations per firm is eighteen.

two reasons. First, different states have different levels of R&D tax credits and corporation tax, which will differentially affect firms depending on their cross-state distribution of R&D activity. We use Wilson's (2009) estimates of state-specific R&D tax prices, combined with our estimates of the cross-state distribution of each firm's R&D, to calculate the "state R&D tax price."[25] Second, we follow Hall (1992) and construct a firm-specific user cost using the federal rules. This has a firm-specific component, in part because the definition of what qualifies as allowable R&D for tax purposes depends on a firm-specific "base."[26]

A concern with using even these tax policy changes as instruments is that they may be endogenous to shocks to the economic environment. We discuss this in detail in Appendix B.3. To summarize, the existing literature suggests a large degree of randomness regarding the introduction and level of R&D tax credits, and we could find no statistical evidence that changes in economic conditions (such as lagged changes in state R&D or GDP) predicted the R&D policy. We use these tax policy instruments to predict R&D, and then use these predicted values weighted up by *SIC* and *TECH* distance as instruments for the two spillover variables in the second stage equations (correcting the standard errors appropriately). Note that the spillover terms are being instrumented by the values of other firms' tax prices, weighted by their distance in technology and product market space.

Finally, note that although our baseline models are static, we show that the empirical results are robust to specifications that allow for more flexible dynamic specifications.

4.2. *Market Value Equation*

We adopt a simple linearization of the value function introduced by Griliches (1981) augmented with our spillover terms:

$$\ln\left(\frac{V}{A}\right)_{it} = \ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it}\right) + \gamma_2 \ln SPILLTECH_{it} + \gamma_3 \ln SPILLSIC_{it} + \gamma_4 X_{it}^V + \eta_i^V + \tau_t^V + \upsilon_{it}^V, \tag{4.3}$$

where V is the market value of the firm, A is the stock of non-R&D assets, G is the R&D stock, and the superscript V indicates that the parameter is from the market value equation. One reason for the deviation of V/A ("Tobin's average Q") from unity is the R&D intensity of different firms. If $\gamma_1(G/A)$

[25]We use the location of a firm's inventors, identified from the patent database, to estimate the location of R&D (see Griffith, Harrison, and Van Reenen (2006)).

[26]For example, from 1981 to 1989, the base was a rolling average of the previous three years' R&D. From 1990 onward, the base was fixed to be the average of the firm's R&D between 1984 and 1988. See Appendix B.3 for more details.

were "small," we could approximate $\ln(1+\gamma_1(\frac{G}{A})_{it})$ by $\gamma_1(\frac{G}{A})_{it}$, but this will not be a good approximation for many high tech firms, so we approximate $\ln(1+\gamma_1(\frac{G}{A})_{it})$ by a series expansion with higher order terms (denoted by $\phi(\frac{G}{A})$).[27] Empirically, we found that a sixth order series expansion was satisfactory. To mitigate endogeneity, we lag the key right hand side variables by one year so the market value equation is

$$\begin{aligned}(4.4)\qquad \ln\left(\frac{V}{A}\right)_{it} &= \phi\left(\left(\frac{G}{A}\right)_{it-1}\right) + \gamma_2 \ln \mathit{SPILLTECH}_{it-1} \\ &\quad + \gamma_3 \ln \mathit{SPILLSIC}_{it-1} + \gamma_4 X_{it}^V + \eta_i^V + \tau_t^V + \upsilon_{it}^V.\end{aligned}$$

4.3. *Patent Equation*

We estimate count data models of future citation-weighted patents (P_{it}) using a Negative Binomial model:

$$\begin{aligned}(4.5)\qquad P_{it} &= \exp\big(\lambda_1 \ln G_{it-1} + \lambda_2 \ln \mathit{SPILLTECH}_{it-1} \\ &\quad + \lambda_3 \ln \mathit{SPILLSIC}_{it-1} + \lambda_4 X_{it}^{\mathrm{P}} + \eta_i^{\mathrm{P}} + \tau_t^{\mathrm{P}} + \upsilon_{it}^{\mathrm{P}}\big).\end{aligned}$$

We use the "pre-sample mean scaling" method of Blundell, Griffith, and Van Reenen (1999) to control for fixed effects.[28] This relaxes the strict exogeneity assumption underlying the approach of Hausman, Hall, and Griliches (1984), but we show that both methods yield qualitatively similar results.

4.4. *Productivity Equation*

We estimate a basic R&D augmented Cobb–Douglas production function (Y is output):

$$\begin{aligned}(4.6)\qquad \ln Y_{it} &= \varphi_1 \ln G_{it-1} + \varphi_2 \ln \mathit{SPILLTECH}_{it-1} \\ &\quad + \varphi_3 \ln \mathit{SPILLSIC}_{it-1} + \varphi_4 X_{it}^Y + \eta_i^Y + \tau_t^Y + \upsilon_{it}^Y.\end{aligned}$$

The key variables in X_{it}^Y are the other inputs into the production function—labor and capital. If we measured output perfectly, then the predictions of the

[27]It is more computationally convenient to do the series expansion than estimate by nonlinear least squares because of the fixed effects. We show that results are similar if we estimate by nonlinear least squares.

[28]Essentially, we exploit the fact that we have a long pre-sample history (from 1970 to at least 1980) of patenting behavior to construct its pre-sample average. This can then be used as an initial condition to proxy for unobserved heterogeneity under the assumption that the first moments of all the observables are stationary. Although there will be some finite sample bias, Monte Carlo evidence shows that this pre-sample mean scaling estimator performs well compared to alternative econometric estimators for dynamic panel data models with weakly endogenous variables (see Blundell, Griffith, and Windmeijer (2002)).

marginal effects of *SPILLTECH* and *SPILLSIC* in equation (4.6) would be qualitatively the same as those in the patent equation. Technology spillovers improve TFP, whereas R&D in the product market should have no impact on TFP (conditional on own R&D and other inputs). In practice, however, we measure output as "real sales"—firm sales divided by an industry price index. Because we do not have information on firm-specific prices, this induces measurement error (see Foster, Haltiwanger, and Syverson (2008)). If R&D by product market rivals depresses own revenues (as we would expect), the coefficient on *SPILLSIC* may be negative and the predictions for equation (4.6) are the same as those of the market value equation. Controlling for industry output (as in Klette and Griliches (1996) or de Loecker (2011)) and fixed effects should go a long way toward dealing with the problem of firm-specific prices, and we show that the negative coefficient on *SPILLSIC* becomes insignificantly different from zero once we control for these additional factors.

4.5. *R&D Equation*

We write the R&D intensity equation as

$$\ln\left(\frac{R}{Y}\right)_{it} = \alpha_2 \ln \mathit{SPILLTECH}_{it-1} + \alpha_3 \ln \mathit{SPILLSIC}_{it-1} + \alpha_4 X_{it}^R + \eta_i^R + \tau_t^R + \upsilon_{it}^R. \tag{4.7}$$

This R&D "factor demand" specification could arise from a CES production function with constant returns to scale in production (see Bloom, Griffith, and Van Reenen (2002)), augmented to allow for spillovers. In this interpretation, the user cost of R&D capital is absorbed in the fixed effects and time dummies, but an alternative is to explicitly model the tax adjusted user cost as we do when constructing the instrumental variables described above. We also examine specifications that relax the constant returns assumption, using $\ln R$ as the dependent variable and including $\ln Y$ on the right hand side of equation (4.7).

5. EMPIRICAL RESULTS

5.1. *Market Value Equation*

Table III summarizes the results for the market value equation. In column (1), the specification without any firm fixed effects, the product market spillover variable, *SPILLSIC*, has a positive association with market value and *SPILLTECH* has a negative association with market value.[29] These are both

[29]The coefficients of the other variables in column (1) were close to those obtained from nonlinear least squares estimation. Using OLS and just the first-order term of G/A, the coefficient

TABLE III

COEFFICIENT ESTIMATES FOR TOBIN'S Q EQUATION

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	OLS	OLS	OLS	OLS	OLS	IV 2nd Stage
Distance Measure:	Jaffe	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\ln(SPILLTECH_{t-1})$	−0.064	0.381	0.305		0.903	1.079
	(0.013)	(0.113)	(0.109)		(0.146)	(0.192)
$\ln(SPILLSIC_{t-1})$	0.053	−0.083		−0.050	−0.136	−0.235
	(0.007)	(0.032)		(0.031)	(0.050)	(0.109)
$\ln(\text{R\&D Stock/Capital Stock})_{t-1}$	0.859	0.806	0.799	0.799	0.835	0.831
	(0.154)	(0.197)	(0.198)	(0.198)	(0.198)	(0.197)
						1st Stage F-Tests
$\ln(SPILLTECH_{t-1})$						112.5
$\ln(SPILLSIC_{t-1})$						42.8
Firm fixed effects	No	Yes	Yes	Yes	Yes	Yes
No. observations	9,944	9,944	9,944	9,944	9,944	9,944

Notes: Dependent variable is $\ln(\text{Tobin's Q}) = \ln(V/A)$ is defined as the market value of equity plus debt, divided by the stock of fixed capital. A sixth-order polynomial in $\ln(\text{R\&D Stock/Capital Stock})_{t-1}$ is included, but only the first term is shown for brevity. Standard errors in brackets are robust to arbitrary heteroskedasticity and first-order serial correlation using the Newey–West correction. A dummy variable is included for observations where lagged R&D stock is zero. All columns include a full set of year dummies and controls for current and lagged industry sales in each firm's output industry. Column (6) uses instrumental variable estimation. "1st Stage F-Tests" are the joint significance of the excluded tax-based instrumental variables ($\ln(TECHTAX)$ and $\ln(SICTAX)$) from each first stage of the endogenous variables, $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$. See Appendix B.3 for details. In column (6), we also control for the firm's own federal and state R&D tax credit values.

contrary to the predictions of the theory. When we allow for fixed effects in column (2), the estimated coefficients on *SPILLTECH* and *SPILLSIC* switch signs and are consistent with the theory.[30] Conditional on technology spillovers, R&D by a firm's product market rivals depresses its stock market value, as investors expect that rivals will capture future market share and/or depress price-cost margins. A ten percent increase in *SPILLTECH* is associated with a 3.8% increase in market value, and a ten percent increase in *SPILLSIC* is associated with a 0.8% reduction in market value.

It is also worth noting that, in column (3), when *SPILLSIC* is omitted, the coefficient on *SPILLTECH* declines. The same bias toward zero is illustrated for *SPILLSIC*—if we failed to control for technology spillovers, we would find

on G/A was 0.266, as compared to 0.420 under nonlinear least squares. This suggests that a first-order approximation is not valid since G/A is not "small"—the mean is close to 50% (see Table II). However, our main results on *SPILLTECH* and *SPILLSIC* are robust to using a first-order linear expansion in G/A. For example, for our preferred column (2) specification, we find a coefficient (*standard error*) of 0.391 (*0.114*) and −0.082 (*0.032*) on *SPILLTECH* and *SPILLSIC*, respectively.

[30]The fixed effects are highly jointly significant, with a p-value < 0.001. The Hausman test also rejects the null of random effects versus fixed effects (p-value $= 0.02$).

no statistically significant impact of product market rivalry in column (4). It is only by allowing for both spillovers simultaneously that we are able to identify their individual impacts.[31] In column (5), we re-estimate the fixed effect specification of column (2) using our Mahalanobis distance measures. We find that the coefficient on *SPILLTECH* rises, suggesting that, by more accurately weighting distances between technology fields, the Mahalanobis spillover metric has substantially reduced attenuation bias. The coefficient on *SPILLSIC* in column (5) is also larger in absolute terms.

In the final column, we treat *SPILLTEC* and *SPILLSIC* as endogenous and use R&D tax prices as instrumental variables. The first stage is presented in Appendix Table A.I of the Supplemental Material, and shows that the excluded instruments are strong. The second stage coefficients on the spillover terms in column (6) of Table III are correctly signed and significant with absolute magnitudes larger than the baseline column (2).

5.2. *Patent Equation*

Table IV presents the estimates for citation-weighted patents equation. Column (1) shows that high R&D firms are more likely to produce patents. More interestingly, *SPILLTECH* has a positive and significant association with patenting, indicating the presence of technology spillovers. By contrast, the product market rivalry term, *SPILLSIC*, has a much smaller and statistically insignificant coefficient.

In column (2), we control for firm fixed effects by using the Blundell, Griffith, and Van Reenen (1999) method of conditioning on the pre-sample, citation-weighted patents. Allowing for fixed effects reduces the coefficient on *SPILLTECH*, but it remains positive and significant.[32] In column (3), we include a lagged dependent variable. There is strong persistence in patenting behavior, but *SPILLTECH* retains a large and significant coefficient. As with Table III, when we use the Mahalanobis measures in column (4), the coefficient on technology spillovers increases. Treating R&D spillovers as endogenous in the final column does not much change the coefficients from column (2).[33]

[31]We also tried an alternative specification that introduces current (not lagged) values of the two spillover measures, and estimated it by instrumental variables using lagged values as instruments. This produced similar results. For example, estimating the fixed effects specification in column (2) in this manner (using instruments from $t-1$) yielded a coefficient (*standard error*) on *SPILLTECH* of 0.401 (*0.119*) and on *SPILLSIC* of −0.094 (*0.033*).

[32]When using unweighted patent counts, the coefficient (*standard error*) on *SPILLTECH* was 0.295 (*0.066*) and 0.051 (*0.029*) on *SPILLSIC*.

[33]The results are also robust to using the Hausman, Hall, and Griliches (1984) method of controlling for fixed effects. Using this method on the specification in column (2), we obtain a coefficient (*standard error*) of 0.201 (*0.064)* on *SPILLTECH* and 0.009 (*0.006*) on *SPILLSIC*, which compares to 0.271 (*0.066*) on *SPILLTECH* and 0.081 (*0.035*) on *SPILLSIC* for the same sample using the Blundell, Griffith, and Van Reenen (1999) method.

TABLE IV

COEFFICIENT ESTIMATES FOR THE CITE-WEIGHTED PATENT EQUATION

	(1)	(2)	(3)	(4)	(5)
Specification:	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin. IV 2nd Stage
Distance Measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\ln(SPILLTECH)_{t-1}$	0.518	0.468	0.417	0.530	0.407
	(0.096)	(0.080)	(0.056)	(0.070)	(0.059)
$\ln(SPILLSIC)_{t-1}$	0.045	0.056	0.043	0.053	0.037
	(0.042)	(0.037)	(0.026)	(0.037)	(0.028)
$\ln(\text{R\&D Stock})_{t-1}$	0.500	0.222	0.104	0.112	0.071
	(0.048)	(0.053)	(0.039)	(0.039)	(0.020)
$\ln(\text{Patents})_{t-1}$			0.420	0.425	0.423
			(0.020)	(0.020)	(0.020)
Pre-sample fixed effect		0.538	0.292	0.276	0.301
		(0.046)	(0.033)	(0.033)	(0.032)
					IV 1st Stage F-Tests
$\ln(SPILLTECH)_{t-1}$					74.6
$\ln(SPILLSIC)_{t-1}$					15.0
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. observations	9,023	9,023	9,023	9,023	9,023

Notes: Dependent variable is Cite-weighted patents. Estimation is conducted using the Negative Binomial model. Standard errors (in brackets) allow for serial correlation through clustering by firm. A full set of time dummies, four digit industry dummies, and lagged firm sales are included in all columns. A dummy variable is included for observations where lagged R&D stock equals zero (all columns) or where lagged patent stock equals zero (column (3)). Columns (2) to (5) include the "pre-sample mean scaling approach" to estimate fixed effects of Blundell, Griffith, and Van Reenen (1999). The Negative Binomial IV specification in column (5) implements a control function approach which includes the first five terms of the expansion of the residual for the first stage regressions. "1st Stage F-Tests" are the joint significance of the excluded tax-based instrumental variables ($\ln(TECHTAX)$ and $\ln(SICTAX)$) from each first stage of the endogenous variables, $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$. See Appendix B.3 for details.

The coefficient on *SPILLSIC* is statistically insignificant and much smaller than *SPILLTECH* throughout Table IV, which is consistent with our basic model.

5.3. *Productivity Equation*

Table V contains the results for the production function. The OLS results in column (1) suggest that we cannot reject constant returns to scale in the firm's own inputs (the sum of the coefficients on capital, labor, and own R&D is 0.995). The spillover terms are perversely signed, however, with negative and significant signs on both spillover terms. Including fixed effects in column (2) changes the results: *SPILLTECH* is positive and significant and *SPILLSIC* becomes insignificant. This pattern is consistent with the theory and the results from the patents equation where *SPILLSIC* is also insignificant (although with a positive coefficient). The significantly negative coefficient on *SPILLSIC* in column (1) could be due to rival R&D having a negative effect on prices, and

TABLE V

COEFFICIENT ESTIMATES FOR THE PRODUCTION FUNCTION

	(1)	(2)	(3)	(4)	(5)
Specification:	OLS	OLS	OLS	OLS	IV 2nd Stage
Distance Measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\ln(SPILLTECH)_{t-1}$	−0.022	0.191	0.186	0.264	0.206
	(0.009)	(0.046)	(0.045)	(0.064)	(0.081)
$\ln(SPILLSIC)_{t-1}$	−0.016	−0.005		−0.007	0.030
	(0.004)	(0.011)		(0.021)	(0.054)
$\ln(\text{Capital})_{t-1}$	0.288	0.154	0.153	0.156	0.152
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
$\ln(\text{Labor})_{t-1}$	0.644	0.636	0.636	0.637	0.639
	(0.012)	(0.015)	(0.015)	(0.015)	(0.016)
$\ln(\text{R\&D Stock})_{t-1}$	0.061	0.043	0.042	0.043	0.041
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
					1st Stage F-Statistic
$\ln(SPILLTECH)_{t-1}$					112.4
$\ln(SPILLSIC)_{t-1}$					51.2
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. observations	9,935	9,935	9,935	9,935	9,935

Notes: Dependent variable is ln(Sales). Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for first-order serial correlation using the Newey–West procedure. Industry price deflators are included and a dummy variable for observations where lagged R&D equals to zero. All columns include a full set of year dummies and controls for current and lagged industry sales in each firm's output industry. Column (5) uses instrumental variable estimation. "1st Stage F-Statistic" are the joint significance of the excluded tax-based instrumental variables ($\ln(TECHTAX)$ and $\ln(SICTAX)$) from each first stage of the endogenous variables, $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$. See Appendix B.3 for details.

depressing a firm's revenue. In principle, these price effects should be controlled for by the industry price deflator, but if there are firm-specific prices, then the industry deflator will be insufficient. If the deviation between firm and industry prices is largely time invariant, however, the fixed effects should control for this bias. This is consistent with what we observe in column (2)—when fixed effects are included, the negative marginal effect of *SPILLSIC* disappears. The third column drops the insignificant *SPILLSIC* term, and is our preferred specification. In column (4), we re-estimate the results using the Mahalanobis measure, and observe an increase of the coefficient on technology spillovers. This coefficient on *SPILLTECH* in the final column, which treats R&D spillovers as endogenous, is similar to the basic specification of column (2).

A concern is heterogeneity across industries in the production function coefficients, so we investigated allowing all inputs (labor, capital, and R&D) to have different coefficients in each two digit industry. In this specification, *SPILLTECH* remained positive and significant at conventional levels.[34] We also experimented with using an estimate of value added instead of sales as the dependent variable, which led to a similar pattern of results.[35]

5.4. *R&D Equation*

Table VI presents the results for the R&D equation. In column (1), there is a large, positive, and statistically significant coefficient on *SPILLSIC*, which persists when we include fixed effects. This indicates that own and product market rivals' R&D are strategic complements. Similar results are obtained if we use ln(R&D) as the dependent variable and include ln(sales) as a right hand side

TABLE VI

COEFFICIENT ESTIMATES FOR THE R&D EQUATION

	(1)	(2)	(3)	(4)	(5)
Specification:	OLS	OLS	OLS	OLS	IV 2nd Stage
Distance Measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\ln(SPILLTECH)_{t-1}$	0.079	0.100	−0.049	−0.176	0.138
	(0.018)	(0.076)	(0.042)	(0.101)	(0.122)
$\ln(SPILLSIC)_{t-1}$	0.374	0.083	0.034	0.224	−0.022
	(0.013)	(0.034)	(0.019)	(0.048)	(0.071)
$\ln(\text{R\&D/Sales})_{t-1}$			0.681		
			(0.015)		
					IV 1st stage F-tests
$\ln(SPILLTECH)_{t-1}$					190.7
$\ln(SPILLSIC)_{t-1}$					38.0
Firm fixed effects	No	Yes	No	Yes	Yes
No. observations	8,579	8,579	8,387	8,579	8,579

Notes: Dependent variable is ln(R&D/Sales). Standard errors (in brackets) are robust to arbitrary heteroskedasticity and serial correlation using Newey–West corrected standard errors. All columns include a full set of year dummies and controls for current and lagged industry sales in each firm's output industry. Column (5) uses instrumental variable estimation. "1st Stage F-Tests" are the joint significance of the excluded tax-based instrumental variables (ln(*TECHTAX*) and ln(*SICTAX*)) from each first stage of the endogenous variables, ln(*SPILLTECH*) and ln(*SPILLSIC*). See Appendix B.3 for details. In column (5), we also include the firm's own federal and state R&D tax credit values.

[34]*SPILLTECH* took a coefficient (*standard error*) of 0.101 (*0.046*) and *SPILLSIC* remained insignificant with 0.008 (*0.012*). Including a full set of two digit industry time trends also led to the same findings. In this specification, the coefficient (*standard error*) on *SPILLTECH* was 0.093 (*0.048*).

[35]Using value added as the dependent variable, the coefficient (*standard error*) on *SPILLTECH* was 0.188 (*0.053*) and on *SPILLSIC* was −0.023 (*0.013*). More generally, using real sales as the dependent variable and including materials on the right hand side generated a coefficient (*standard error*) on *SPILLTECH* of 0.127 (*0.039*) and on *SPILLSIC* of −0.007 (*0.010*).

variable.[36] In column (3), we include a lagged dependent variable,[37] and in column (4), we use the Mahalanobis distance measures. In both specifications, we find that *SPILLSIC* remains positive at the 10% level or greater, with a long-run coefficient larger than in column (2). In column (5), we treat spillovers as endogenous and find that they are insignificant. Across Table VI, the coefficient on *SPILLTECH*, which is theoretically of ambiguous sign, is not robust. It is insignificant in columns (2), (3), and (5), positive and significant in column (1), and negative and (weakly) significant in column (4).

The evidence from Table VI provides some evidence suggesting that R&D spending of product market rivals is a strategic complement of own R&D, as many IO models assume but rarely test.[38] However, treating spillovers as endogenous (as we do in the final column) weakens this conclusion, which suggests that the positive covariance of own R&D and *SPILLSIC* may be driven by common shocks.

5.5. *Summary of Basic Empirical Results*

Table VII compares our empirical findings against the predictions of the theoretical model. Despite its simplicity, our model performs surprisingly well, with all six predictions supported by the data. R&D by neighbors close in technology space is associated with higher market value, patenting, and TFP. R&D by neighbors close in product market space is associated with lower market value and no effect on patents or TFP. These results hold true whether we use the Jaffe or Mahalanobis version of technology and product market distance, and whether or not we treat R&D spillovers as endogenous. If anything, using the Mahalanobis measure or IV approach tends to produce larger coefficients than the simpler baseline OLS Jaffe results, which is consistent with the view that they suffer from less attenuation bias due to measurement error.[39]

[36]The coefficient (*standard error*) on *SPILLSIC* was 0.082 (*0.034*) and on *SPILLTECH* was 0.121 (*0.072*).

[37]We checked that the results were robust to allowing sales and lagged R&D to be endogenous by re-estimating the R&D equation using the Blundell and Bond (1998) GMM "system" estimator. The qualitative results were the same. For example, in the specification of the R&D equation in Table VI, column (3), we obtained a coefficient (*standard error*) on the lagged dependent variable of 0.671 (*0.016*), on *SPILLSIC* of 0.050 (*0.025*), and on *SPILLTECH* of −0.109 (*0.034*). This is reasonably similar to the baseline model where the equivalent coefficients were 0.681, 0.034, and −0.049, respectively. We could not reject the hypothesis of no first-order serial correlation in the levels of the error term, which is a necessary condition for instrument validity (p-value = 0.531).

[38]We know of only two papers that empirically test for patent races, one on pharmaceuticals and the other on disk drives (Cockburn and Henderson (1994), and Lerner (1997)), and the evidence is mixed. However, neither of these papers allows for both technology spillovers and product market rivalry.

[39]We also estimated IV versions of the Mahalanobis measures, which produced results similar to the OLS Mahalanobis estimates.

TABLE VII

COMPARISON OF EMPIRICAL RESULTS TO MODEL WITH TECHNOLOGICAL SPILLOVERS AND PRODUCT MARKET RIVALRY

(1)	(2) Partial Correlation	(3) Theory	(4) Empirics Jaffe	(5) Empirics Mahalanobis	(6) Empirics Jaffe, IV	(7) Consistency?
$\partial V_0/\partial r_\tau$	Market value with *SPILLTECH*	Positive	0.381**	0.903**	1.079***	Yes
$\partial V_0/\partial r_m$	Market value with *SPILLSIC*	Negative	−0.083**	−0.136**	−0.235**	Yes
$\partial k_0/\partial r_\tau$	Patents with *SPILLTECH*	Positive	0.417**	0.530**	0.407**	Yes
$\partial k_0/\partial r_m$	Patents with *SPILLSIC*	Zero	0.043	0.053	0.037	Yes
$\partial y_0/\partial r_\tau$	Productivity with *SPILLTECH*	Positive	0.191**	0.264**	0.206**	Yes
$\partial y_0/\partial r_m$	Productivity with *SPILLSIC*	Zero	−0.005	−0.007	0.030	Yes
$\partial r_0/\partial r_\tau$	R&D with *SPILLTECH*	Ambiguous	0.100	−0.176*	0.138	
$\partial r_0/\partial r_m$	R&D with *SPILLSIC*	Ambiguous	0.083**	0.224**	−0.022	

Notes: The theoretical predictions are for the case of technological spillovers. The empirical results are from the static fixed effects specifications for each of the dependent variables. ** denotes significance at the 5% level and * denotes significance at the 10% level (note that coefficients are as they appear in the relevant tables, not marginal effects).

6. EXTENSIONS AND ROBUSTNESS

In this section, we present five major extensions to our empirical investigations. First, we allow the choice of technology class to be endogenous. Second, we examine the importance of geographic distance for spillovers. Third, we examine a variety of other measures of spillovers. Fourth, we look at how the strength of technology spillovers and product market rivalry varies across sectors. Finally, we analyze the private and social returns to R&D implied by our parameter estimates so as to shed light on the major policy issue of whether there is under-investment in R&D.

6.1. *Endogenizing Firm Choice of Technology Classes*

The two stage game of Section 2 took a firm's distribution of activity across technology classes as exogenous. We extend this to consider a "stage 0," where a firm chooses in which fields to focus its R&D efforts. This defines its technological profile and is fixed for the rest of the game. Considering any pair of firms, we generate a "co-agglomeration" index, first suggested by Ellison and Glaeser (1997), to measure the degree to which industries and firms were co-located or co-agglomerated in the same geographic areas. We will discuss geographical concerns explicitly in the next subsection, but since in our basic model we focused only on closeness in technology and product markets, we continue to do so in this subsection. In the context of technological areas, the co-agglomeration index, γ_{ij}^{C}, between a pair of firms, i and j, is

$$TECH_{ij}^{EG} = \gamma_{ij}^{C} \equiv \frac{\sum_{\tau}(T_{i\tau} - x_{\tau})(T_{j\tau} - x_{\tau})}{1 - \sum_{\tau} x_{\tau}^{2}}, \tag{6.1}$$

where $T_{i\tau}$ is the proportion of all firm i patents in technology class τ and x_{τ} is the share of total patents in the technology class τ.

Appendix E of the Supplemental Material draws upon Ellison, Glaeser, and Kerr (2007, 2010) to show that γ_{ij}^{C} is the expected value of spillovers (per unit of R&D) in an explicit model of the choice of technology classes. In this model, firms choose where to locate their R&D labs across technology classes. The profits from locating a lab in a particular class depend on the (common to all firms) technological opportunities in that class, a purely idiosyncratic term, and the potential spillovers from another lab located in the same class. The latter arises because some labs (and firms) are intrinsically better at learning from each other and will therefore tend to co-locate in a class; this might be because they both have some previous connection (e.g., the firms' Chief Technology Officers may both have studied together at university). Under the set of assumptions in Appendix E, patterns of co-location reveal this spillover potential.

Note that this model is not appropriate for examining product market rivalry. Firms will endogenously choose to locate in areas where they may obtain technological spillovers, which leads to clustering in certain classes for pairs of firms. But with product market competition, firms will want to be in *different* product classes as their products are substitutes.

We implement this idea by replacing our previous measure of proximity, $TECH_{ij}$, with $TECH_{ij}^{EG}$ and reconstructing *SPILLTECH*. Equation (6.1) is obviously closely related to $TECH_{ij}$: the numerator is the same as Jaffe's except we center it at the mean of the technological profile of all firms (x_{τ}). The denominator is different, however, as we do not divide by the variance of each firm's profile, but rather the overall variance. The empirical correlation between the two measures of *SPILLTECH* is 0.731 and highly significant.

Panel B of Table VIII gives the results from our baseline specifications with this new measure. The qualitative results are similar to those in the baseline results in Panel A. There are significant technological spillovers in the value equation and production function. Product market rivalry is indicated by the negative and significant coefficient on *SPILLSIC* in the value equation, and there are signs of significant strategic complementarity of R&D in column (4). As in the main results, *SPILLSIC* is insignificant for patents and productivity.

TABLE VIII

ALTERNATIVE WAYS OF MEASURING SPILLOVERS

Dependent Variable:	(1) Tobin's Q	(2) Cite Weighted Patents	(3) Real Sales	(4) R&D/Sales
A. Baseline (Summarized From Tables III–VI Above)				
$\ln(SPILLTECH)_{t-1}$	0.381	0.468	0.191	0.100
	(0.113)	(0.080)	(0.046)	(0.076)
$\ln(SPILLSIC)_{t-1}$	−0.083	0.056	−0.005	0.083
	(0.032)	(0.037)	(0.011)	(0.034)
Observations	9,944	9,023	9,935	8,579
B. Spillovers Based on Ellison–Glaeser Co-Agglomeration Method				
$\ln(SPILLTECH^{EG})_{t-1}$	0.961	0.123	0.179	−0.082
	(0.181)	(0.562)	(0.073)	(0.109)
$\ln(SPILLSIC^{EG})_{t-1}$	−0.087	0.066	0.005	0.107
	(0.031)	(0.042)	(0.012)	(0.033)
Observations	9,944	9,023	9,935	8,579
C. Geographically Based Measure of Spillovers				
$\ln(SPILLTECH^{GEOG})_{t-1}$	1.314	0.037	0.117	
	(0.176)	(0.053)	(0.066)	
$\ln(SPILLTECH)_{t-1}$	−0.559	0.391	0.101	
	(0.163)	(0.069)	(0.060)	
$\ln(SPILLSIC^{GEOG})_{t-1}$	0.110			−0.041
	(0.078)			(0.094)
$\ln(SPILLSIC)_{t-1}$	−0.175			0.135
	(0.062)			(0.086)
Observations	9,944	9,122	10,018	8,579
D. Spillovers Based on Jaffe Covariance/Exposure Distance Metrics				
$\ln(SPILLTECH^{J\text{-}COV})_{t-1}$	0.282	0.470	0.142	0.096
	(0.102)	(0.084)	(0.041)	(0.068)
$\ln(SPILLSIC^{J\text{-}COV})_{t-1}$	−0.078	0.047	−0.006	0.084
	(0.032)	(0.026)	(0.012)	(0.035)
Observations	9,944	9,023	9,949	8,579

Notes: Panel A gives the baseline results: value equation in column (1) corresponds to Table III, column (2); patents equation in column (2) corresponds to Table IV, column (2); productivity equation in column (3) corresponds to Table V, column (2), and R&D equation in column (4) corresponds to Table VI, column (2). In Panel B, *TECH* is measured by the co-agglomeration index of Ellison and Glaeser (1997). Otherwise, all specifications are the same as in Panel A. In Panel C, the variable $SPILLTECH^{GEOG}$ uses the patenting distance weighting function between firms to scale their technology overlap. The variable $SPILLSIC^{GEOG}$ uses the sales distance function between two firms to scale their product market overlap (see Section 6.2). The equations all use the preferred specifications from the main tables (i.e., column (1) corresponds to Table III, column (2); column (2) corresponds to Table IV, column (2); column (3) corresponds to Table V, column (3), and column (4) corresponds to Table VI, column (2)). In Panel D, we use the same specifications as Panel A except we substitute the Jaffe-Covariance index for both technology ($SPILLTECH^{J\text{-}COV}$) and product market spillovers ($SPILLSIC^{J\text{-}COV}$), which is empirically identical to using the Exposure in our log-linear specification with ln(R&D) as an explanatory variable.

The main difference between Panels A and B is that *SPILLTECH* is insignificant in the patents equation. The coefficient is correctly signed (positive), however, and the standard error is large, encompassing the estimate in Panel A. A more minor point is that the coefficient on *SPILLTECH* is much larger in the market value equation than for the Jaffe measure, but close to the estimates from the Mahalanobis measure and IV estimates (columns (5) and (6) of Table III).

Overall, then, the alternative measure of distance (co-agglomeration) delivers qualitatively similar conclusions to our baseline measures.

6.2. *Geographic Spillovers*

Until now, we have abstracted from explicit geographical considerations, but spatial closeness may have an effect on technology spillovers and product market rivalry. To incorporate the impact of geographic distance on technological spillovers, we start with the state of location of the first inventor on every patent, or foreign country for non-U.S. based inventors. For each firm, we then define the vector $L_i^{\mathrm{T}} = (L_{i1}^{\mathrm{T}}, L_{i2}^{\mathrm{T}}, \ldots, L_{i136}^{\mathrm{T}})$, where $L_{i\tau}^{\mathrm{T}}$ is the share of patents of firm i in location g, which runs from 1 to 136, reflecting the 50 different U.S. states and 86 foreign countries across which we observe the distribution of patents. The geographical technological closeness measure, $GEOG_{ij}^{\mathrm{T}}$ $(i \neq j)$, is calculated as the uncentered correlation between all firm i, j pairings:

$$(6.2)\qquad GEOG_{ij}^{\mathrm{T}} = \frac{(L_i^{\mathrm{T}} L_j^{\mathrm{T}\prime})}{(L_i^{\mathrm{T}} L_i^{\mathrm{T}\prime})^{1/2}(L_j^{\mathrm{T}} L_j^{\mathrm{T}\prime})^{1/2}}.$$

We perform a similar exercise for product markets using the regional breakdown of sales in companies' accounts. Because this is not always reported at the same level of aggregation—for example, a firm may report 50% of sales being in any of "England," "Britain," or "Europe"—we aggregate this by nine geographic regions (Africa, Asia, Australasia, Europe, Middle East, Non-U.S. North America, South America, Ex-Soviet Block, and the U.S.). Using these data, we can define a vector of a firm's location of sales, $L_i^{\mathrm{S}} = (L_{i1}^{\mathrm{S}}, L_{i2}^{\mathrm{S}}, \ldots, L_{i9}^{\mathrm{S}})$, and a geographical sales closeness measure, $GEOG_{ij}^{\mathrm{S}}$ $(i \neq j)$:

$$(6.3)\qquad GEOG_{ij}^{\mathrm{S}} = \frac{(L_i^{\mathrm{S}} L_j^{\mathrm{S}\prime})}{(L_i^{\mathrm{S}} L_i^{\mathrm{S}\prime})^{1/2}(L_j^{\mathrm{S}} L_j^{\mathrm{S}\prime})^{1/2}}.$$

With these two measures, we can then define geographically distance-weighted technology and product market spillover measures:

$$(6.4)\qquad SPILLTECH_{it}^{\mathrm{GEOG}} = \sum_{j \neq i} TECH_{ij} \times GEOG_{ij}^{\mathrm{T}} \times G_{jt},$$

$$SPILLSIC_{it}^{\mathrm{GEOG}} = \sum_{j \neq i} SIC_{ij} \times GEOG_{ij}^{\mathrm{S}} \times G_{jt}.$$

Finally, we include these measures into our baseline regressions alongside our standard measures of technology and product market spillovers. If geographic distance matters, then we would expect our geographically weighted measures to empirically dominate, while if geographic distance is unimportant for spillovers, then the basic measure should dominate.

Panel C of Table VIII reports the results. In the first three columns, the coefficient on geographically weighted technology spillovers ($SPILLTECH_{it}^{\mathrm{GEOG}}$) has the expected positive sign and is significant (at the 10% level or greater) for both market value and productivity. This suggests some benefits to being geographically close in order to capture knowledge spillovers, as in Jaffe, Trajtenberg, and Henderson (1993). By contrast, our geographically weighted product market spillovers are always insignificant, suggesting that product market interactions are not that sensitive to regional interactions. This is consistent with the idea that the firms in our sample (large publicly listed U.S. firms) operate in mainly quite globalized product market where physical distance is relatively unimportant.[40] Lychagin, Pinkse, Slade, and Van Reenen (2010) implemented a related but distinct method of examining geographical R&D spillovers (using more disaggregated county-level data) in the presence of technological spillovers and product market rivalry. They also found that geographical spillovers are important in increasing productivity.

6.3. *Other Alternative Distance Measures*

There are many ways to construct spillover models; Section 7 has a formal comparison. In this subsection, we show that our results are empirically robust to different possible measures.[41]

6.3.1. *Jaffe Covariance and Exposure Based Measures of Spillovers*

In Section 3.1, we discussed the theoretical basis of the Jaffe (1986) distance based measure of spillovers and also derived two alternative measures that we labeled the Jaffe Covariance and Exposure measures. Although closer to the formal model, these measures had some statistically unattractive properties, such as lack of robustness to arbitrary aggregations of technology classes, which

[40] Of course, given the coarseness of our measure of product market geography, another interpretation is that our geographic market closeness measure is too noisy to get a significant interaction. This is certainly possible, although we would still expect to see some muted results on the interaction if geographic distance really mattered for product market interactions. The robust zero effect across all columns suggests it does not.

[41] As another robustness test, we also reset the *TECH* and *SIC* distance measure to 0 for any firm pairs with both *TECH* and *SIC* above 0.1. This allows us to estimate results identifying only firm pairs for which firms are either close in technology space or product space but not both. Doing this, we find first that *TECH* and *SIC* have a correlation of −0.024 (so are now orthogonalized in the data), and second that our main results are robust (see Table A.III, Panel D).

is why we preferred the conventional Jaffe measure as our baseline. Panel D of Table VIII shows what happens to our results if we use these measures instead (for both technology and product market spillover measures). Only one set of results are reported because, as noted in Section 3.1, our log-linear specifications including firm R&D means the Jaffe Covariance and Exposure measures are empirically identical. Reassuringly, we find the results are quite stable, illustrating that it is the numerator of the distance metric that is driving our results, rather than the normalization. The only slight difference is that the *SPILLSIC* coefficient is significant in the patents equation, whereas it was insignificant in the baseline results. In Appendix A.3 of the Supplemental Material, we present an extended model, where patents are endogenously chosen, that may rationalize such a positive effect.

6.3.2. *An Alternative to the Compustat Segment Data: The BVD Data Set*

The finance literature has debated the extent to which the breakdown of firm sales into four digit industries from the Compustat Segment Data Set is reliable. To address this concern, we used an alternative data source, the BVD (Bureau Van Dijk) database. This contains information on the size, industry, and global ultimate owner of about ten million establishments in North America and Europe. We match these to Compustat, creating company trees: a breakdown of each parent firm's activity according to the activity and size of its subsidiaries. The correlation between the Compustat Segment and BVD Data Set measures is high (e.g., within-firm correlation of ln(*SPILLSIC*) is 0.737). The empirical results (Panel B in Table A.III of the Supplemental Material) are also similar to the earlier tables, confirming the key findings of technology spillovers, product market rivalry, and strategic complementarity of R&D.

6.3.3. *Disaggregating Patent Classes*

Thompson and Fox-Kean (2005) have suggested that the three digit patent class may be too coarse, and that a finer disaggregation is better for measuring spillovers. As Henderson, Jaffe, and Trajtenberg (2005) pointed out, finer disaggregation of patents classes is not necessarily superior, as the classification is subject to a greater degree of measurement error.[42] Nonetheless, to check robustness, we reconstructed the (Jaffe) distance metric using six digit patent classes and then used that measure to construct a new pool of technology spillovers. The empirical results are robust for all four equations (Panel C in Table A.III).

[42]The information is only available from 1976 (compared to 1963 for all patents), has more missing values, and contains a greater degree of arbitrary allocation by the patent examiners.

6.4. *Econometric Results for Three High-Tech Industries*

We used both the cross-firm and cross-industry variation (over time) to identify our two spillover effects. A straightforward extension of the methodology is to examine particular industries. This is difficult to do for every sector given the size of our data set. Nevertheless, it would be worrying if the basic theory was contradicted in the high-tech sectors, as this would suggest that our results might be due to biases induced by pooling across heterogeneous sectors. We examine in more detail the three most R&D intensive sectors where we have a sufficient number of firms to estimate our key equations: computer hardware, pharmaceuticals, and telecommunications equipment (see Appendix F of the Supplemental Material for details). Overall, the qualitative results are robust: significant technology spillovers are found in all three sectors, with larger coefficients than in the pooled results, and the coefficient on the product market rivalry term is always negative in the value equation. However, there is also some interesting heterogeneity. First, the magnitudes of the technology spillover and product market rivalry effects vary. Second, we find statistically significant product market rivalry effects of R&D on market value in only two of the three industries studied (they are not present in telecommunications). Finally, there is evidence of strategic complementarity in R&D for computers and pharma, but not for telecommunications.

6.5. *Estimates of the Private and Social Returns to R&D*

6.5.1. *Methodology*

In this subsection, we use our coefficient estimates to calculate the private and social rates of return to R&D for the whole sample and for different subgroups of firms. In doing this, we are making the stronger assumption that the coefficients we estimated in the empirical work have a structural interpretation and can be used for policy purposes. This goes beyond the simple qualitative predictions of the model that we tested in the empirical work. We are assuming here that the functional forms are correct, the distance metrics can be interpreted quantitatively, and the estimated coefficients are causal. For all these reasons, this discussion is inherently more speculative.

With these caveats in mind, we define the marginal social return (MSR) to R&D for firm i as the increase in *aggregate output* generated by a marginal increase in firm i's R&D stock (taking into account the induced changes in R&D by other firms).[43] The marginal private return (MPR) is defined as the increase

[43]This is the conventional definition adopted by researchers using a production function framework. Nonetheless, it is worth pointing out that this definition does not fully capture consumer surplus, and thus underestimates the full social return from R&D. The extent of this underestimation depends on how much of the surplus firms can capture and on the price deflators used to convert observed revenues into real output measures, which may vary across different types of firms and industries (Griliches (1979)).

in *firm i's output* generated by a marginal increase in its R&D stock. Both the MSR and MPR refer to gross rates of return, prior to netting out the depreciation of R&D knowledge. Appendix G of the Supplemental Material provides a detailed discussion of how to calculate these rates of return for individual firms within our analytical framework. In the general case, the rates of return for individual firms depend on the details of their linkages to other firms in both the technology and product market spaces. Although we will use the general formulas to compute the returns presented in this subsection, much of the intuition can be understood by examining the special case where all firms are fully symmetric and we abstract from the "amplification" effects arising from mechanisms like strategic complementarity in R&D. What we mean by fully symmetric is that all firms are the same size in sales and R&D stocks, and are identically linked with other firms in both the technology and product market spaces. In this special case, the marginal social return can be written simply as

$$\text{MSR} = \left(\frac{Y}{G}\right)(\varphi_1 + \varphi_2), \tag{6.5}$$

where φ_1 and φ_2 are the coefficients (output elasticities) of the own R&D stock (G) and the pool of technology spillovers (*SPILLTECH*) in the production function, respectively, and Y/G is the ratio of output to the R&D stock.[44] In this formulation, the MSR can be interpreted as a marginal product of a firm's R&D, which reflects both the direct contribution to the firm's own R&D stock (φ_1) and the indirect effect it has by augmenting the stock of technology spillovers enjoyed by all other firms (φ_2). Own R&D increases productivity, so obviously will affect both the private return and social return. R&D by other firms will affect the social return but not the private return. Thus, the larger MSR is, the stronger is the impact of the technology spillovers generated by the firm.

Continuing with the special case, the marginal private return can be expressed as

$$\text{MPR} = \left(\frac{Y}{G}\right)(\varphi_1 - \sigma\gamma_3). \tag{6.6}$$

In equation (6.6), we still include the effect of own R&D on productivity (φ_1) as in the MSR, but now there is also a term in γ_3, the coefficient on *SPILLSIC*

[44]In computing the social returns, it is important to use the elasticity of R&D stock from the production function, φ_2, rather than from the value equation, γ_2. The R&D elasticity in the value function should be larger because it captures both the pure productivity shift due to R&D and the increase in the levels of other variable inputs such as employment, whereas the production function elasticity captures only the productivity effect. This is confirmed by our econometric estimates.

in the market value equation. Recall that this reflects R&D spending by a firm's rivals in the product market. Since $\gamma_3 < 0$, the MPR is larger than simply its contribution to the firm's own R&D stock because of the business stealing effect inherent in oligopoly models. This effect increases the private incentive to invest in R&D by redistributing output between firms, but does not enter the social return calculus and thus is absent from the MSR. The γ_3 coefficient is multiplied by a parameter σ which represents the proportion of the fall in market value from a rival's R&D that comes from reduction in its level of output (this is redistributed to the rival firms) rather than an induced decline in price (which does not benefit rival firms). For the calculations here, we set $\sigma = \frac{1}{2}$.[45]

In this symmetric case with no amplification of R&D, the wedge between the social and private returns depends upon the importance of technology spillovers in the production function (φ_2) relative to rivalry effects in the market value equation (γ_3). The social rate return to R&D can be *either larger or smaller* than the private rate of return, depending on the relative magnitudes of φ_2 and $|\sigma\gamma_3|$. Intuitively, the more important *SPILLTECH* is relative to *SPILLSIC*, the more likely it is that the positive effects of R&D will dominate the negative ones from a social perspective.

In the general case derived in Appendix G and empirically implemented below, the relative returns also depend on the position of all firms in both the technology and product market spaces, but the result continues to hold that the social return to R&D can be either larger or smaller than the private return.

6.5.2. *Results for the Private and Social Return to R&D*

Using our baseline parameter estimates, assuming symmetric firms and no amplification, and evaluating these expressions at the median value of $\frac{Y}{G}$ (which is 2.48), we obtain an estimate of the MSR of 58% ($= 2.48 \times (0.043 + 0.191)$), and an estimate of the MPR of 20.8% ($= 2.48 \times (0.043 + 0.042)$). This calculation shows that, for the sample of firms taken together, the marginal social returns are between two and three times the private returns, indicating under-investment in R&D. The estimated wedge between the social and private return rises from 29.2% ($= 58\% - 20.8\%$) to 39.4% ($= 58\% - 10.6\%$) if we ignore the product market rivalry effect. We can use our estimates of the private and social returns to infer the gap between the observed and the socially optimal level of R&D. To do this, we need an assumption about the price

[45]We need an assumption on the parameter σ in order to back out the implied output redistribution from our estimates of the business stealing effect in the market value equation, which includes both the output and price effects of rivalry. Different oligopoly models will generate different precise values of the scaling parameter, σ. Most oligopoly models we have examined, with standard isoelastic demand and constant marginal cost, generate values of σ less than $\frac{1}{2}$. We argue in Appendix G that a value of $\sigma = \frac{1}{2}$ is conservative, in that it leads us to overestimate the private return and thus underestimate the wedge between private and social returns to R&D.

TABLE IX

PRIVATE AND SOCIAL RETURNS TO R&D

Group of Firms	(1) Closeness Measure	(2) Private Return (%)	(3) Social Return (%)	(4) Wedge Percentage Points	(5) Median Employees	(6) Avg. SIC	(7) Avg. TECH
Closeness Measures							
1. All	Jaffe	20.7	55.0	34.3	3,000	0.015	0.038
2. All	Mahalanobis	27.6	73.7	46.1	3,000	0.030	0.174
3. All	Jaffe, IV	39.3	59.4	20.1	3,000	0.015	0.038
Size Splits							
4. Largest size quartile	Jaffe	21.1	67.1	46.0	29,700	0.015	0.054
5. Second size quartile	Jaffe	20.5	55.0	34.5	5,900	0.012	0.037
6. Third size quartile	Jaffe	20.7	50.8	30.1	1,680	0.016	0.033
7. Smallest size quartile	Jaffe	20.6	47.3	26.6	370	0.018	0.029

Notes: Numbers simulated across all firms in our sample with nonzero R&D capital stocks. We use our "preferred" systems of equations and coefficients as in Table VII. Details of calculations are in Appendix E. Columns (2) and (3) contain the private and social returns to a marginal $ of R&D and column (4) contains the absolute difference between columns (2) and (3). Column (5) reports the median number of employees in each group, and the last two columns report the average closeness measure between firms in product market space (*SIC*) and the average closeness measure in technology space (*TECH*). The first row calculates the private and social returns for the baseline estimates using exogenous R&D and the Jaffe based measures of distance (column (2), Table VII). The second row recalculates this for firms using the Mahalanobis distance measure (column (4), Table VII). The third row recalculates this using the Jaffe closeness measure with the tax credit instruments for firm-level R&D (column (5), Table VII). The next four rows recalculate these figures for firms based on their position in the employment size quartiles.

elasticity of the demand for R&D. Using a price elasticity of unity,[46] and the ratio of MSR to MPR of 2.76, we find that the socially optimal level of R&D is about three times as large as the observed level.

The results for the full calculations of private and social returns, allowing for asymmetric firms and amplification effects, are presented in Table IX. Several important results emerge from this table. First, in the full calculations given in row 1, we find that the gross social returns are estimated at 55% and the gross private returns at 20.7%, again indicating a substantial divergence between social and private returns of 34.3 percentage points. This is surprisingly similar to the results for the symmetric no amplification case discussed above, suggesting that the simple case is not misleading when considering the aggregate effects. Second, row 2 in Table IX shows the results from using the Mahalanobis

[46]Our estimated coefficients on the tax credit variables from the first stage IV regression (column (3), Table A.I), evaluated at the sample means, imply a price elasticity of −0.70 and −2.0 for the federal and state tax credits, respectively, while Bloom, Griffith, and Van Reenen (2002) found a long-run value of −1.1 estimating using cross-country and time variation in R&D tax credits and reported similar values of around unity for other papers in the literature.

distance metric, in which gross social returns are shown to be 46.1 percentage points above private returns. Row 3 shows the IV results, which show the smallest gap between private and social returns, but even here social returns are almost twice as big as private returns.

To calculate an optimal subsidy level, we need to compare the net social and private returns, rather than gross returns, that is, to net out appropriate R&D depreciation. One approach is to assume that social and private returns both have the same depreciation rate, for example, the 15% value we use to calculate the empirical R&D stock, in which case the gap between net social and private returns is the same as the gap between gross returns. However, as Griliches (1979) and Pakes and Schankerman (1984) argued, the social depreciation rate of R&D is likely to be lower than the private rate because private depreciation includes the redistribution of rents across firms, which is not a social loss. If this is so, our estimate of the gap between private and social returns is probably a lower bound to the true gap net of depreciation.

Next, in rows 4–7 of Table IX we split firms by their quartiles of size. We find that larger firms have a *bigger gap* between social and private returns. The reason is that larger firms tend to operate in more populated technology fields, and thus have a higher level of connectivity with other firms in technology space (shown by their higher average *TECH* values: 0.054 in the largest quartile). For this reason, they generate more spillovers at the margin. Smaller firms tend to operate more in technology niches (shown by their lower average *TECH* values: 0.029 in the lowest quartile) and so generate fewer spillovers. Taken at face value, this result would suggest that larger firms should receive more generous R&D subsidies. Of course, technology spillovers are not the only possible justification for government intervention. Other factors—most notably, imperfect capital markets—may argue for a larger subsidy for smaller (or perhaps more reasonably, younger) firms, which are likely to be more severely liquidity-constrained. Our Compustat sample has very few observations from small firms and thus is not informative on this issue.[47] But our finding here does, at least, suggest a reconsideration of the more generous tax credits for smaller firms that are standard in many countries.

7. A COMPARISON OF SPILLOVER MEASURES

In this paper, we have developed and applied a variety of technology spillover measures based on different measures of proximity between firms. We do this primarily to establish the robustness of our main empirical findings,

[47]In the data, 13% of the observations come from firms with fewer than 500 employees, the formal cut-off for smaller and medium sized enterprises. These firms, of course, will be a selected sample, given that they are all publicly quoted.

but it is of independent interest to compare the strengths and weaknesses of these measures. To do this, we propose a series of desirable properties ("axioms") and then evaluate the measures based on these properties.[48] To our knowledge, this is the first attempt to give an "axiomatic" basis for evaluating different measures of technology (and product market) proximity and spillovers.

We propose the following properties for evaluating proximity (and their associated spillover) measures:

1. *EMF*: The index has an economic microfoundation. This property is self-evidently desirable.

2. *SCALE*: The index is invariant (up to a proportionality factor) to rescaling the number of units. If Property 2 did not hold, rankings of firm pairs in terms of proximity depend on the units in which we measure R&D.

3. *WFO*: The index increases in the degree of R&D overlap within a technology field (*within-field overlap*). Property 3 says that, holding constant the share of firm's j's R&D in technology field τ, firm i is more likely to enjoy a knowledge spillover from firm j the larger is the share of firm i's R&D in field τ. Formally, $TECH_{ij}$ is strictly increasing in $n_{i\tau}/n_i$. This is the basic assumption underlying the empirical literature on measuring R&D spillovers.

4. *BFO*: The index increases in the degree of R&D overlap in technologically related fields (*between-field overlap*). Property 4 extends Property 3 to cross-technology field spillovers. For a given share of firm j's R&D in technology field τ, firm i is more likely to enjoy a knowledge spillover from firm j in field τ if it does more R&D in field q whenever fields τ and q are technologically related ($\omega_{\tau q} > 0$).

5. *NOF*: The index is invariant to the allocation of R&D by firm i in fields where firm j does no R&D and which are not technologically related to those in which firm j is active (*non-overlapping fields*). Property 5 says that the technological proximity between two firms should depend only on the extent to which their R&D *overlaps* (i.e., occurs in fields where $\omega_{\tau\nu} > 0$). Formally, let B_1 denote the set of technology fields in which at least one of the firms i and j is active and where $\omega_{\tau q} > 0$ for $(\tau, q) \in B_1$, and let B_2 de-

[48]There is a related approach in the sociology literature on segregation measures. In an influential paper, Massey and Denton (1986) identified five dimensions of (geographic) segregation, related the various existing measures of segregation in the sociology literature to these different dimensions, and then constructed a synthetic measure using factor analysis. The five dimensions are: evenness, exposure, concentration, centralization, and clustering (contiguity). Of these, only exposure and clustering apply to measuring knowledge spillovers. Clustering has been given an economic microfoundation by Ellison and Glaeser, which we discuss in Section 6.1 and Appendix E of the Supplemental Material. Exposure relates to the probability that different members of distinct groups (firms in our context) come into contact with each other, which we develop in Sections 3.1–3.3.

note the complementary set. Let $F_i^{B_1}$ and $F_i^{B_2}$ denote the allocation of firm i's R&D across fields in the set B_1 and B_2, respectively. Property 5 requires that $TECH_{ij}(F_i^{B_1}, F_j^{B_1}, F_i^{B_2}, F_j^{B_2}) = TECH_{ij}(F_i^{B_1}, F_j^{B_1})$ for any allocations $F_i^{B_2}$ and $F_j^{B_2}$.

6. *AGG*: The index is invariant to aggregation of technology fields in which neither firm i nor firm j does R&D. Property 6 states that, if neither firm i nor firm j has R&D activity in a subset of technology fields, their proximity index should be invariant to any aggregation of those fields. Formally, let B_1 denote the set of technology fields in which at least one of the firms i and j is active and where $\omega_{\tau q} > 0$ for $(\tau, q) \in B_1$, and let B_2 denote the set complementary to B_1. Let $B_2^a \subset B_2$ denote a set in which some fields in B_2 are aggregated, and let $TECH_{ij}(B_1, B_2)$ and $TECH_{ij}(B_1, B_2^a)$ be the proximity measure based, respectively, on the set (B_1, B_2) and (B_1, B_2^a). Then $TECH_{ij}(B_1, B_2) = TECH_{ij}(B_1, B_2^a)$. Property 5 implies Property 6, but not vice versa.

7. *ROB*: The index is robust to the aggregation of technology fields in which either firm i or firm j does R&D. Property 7 says that an index is preferred if it is less sensitive to how technology fields are defined (see the discussion in Section 3.1 and Appendix C.1). Formally, let $TECH_{ij}(B_1)$ denote a proximity index based on the set of technology fields B_1. Let B_2 denote a new set of fields in which some subsets $B_1^a \subset B_1$ are aggregated, and where at least one of the firms (i, j) is engaged in the fields B_1^a. Then an index $TECH_{ij}$ is preferred the smaller is the value $|\frac{TECH_{ij}(B_2)}{TECH_{ij}(B_1)} - 1|$.

In Table X, we compare five proximity measures: (1) the standard Jaffe index, (2) our Mahalanobis generalization of the Jaffe index, (3) the Jaffe covariance index, (4) the Exposure index, and (5) the Ellison–Glaeser coagglomeration index. An 'X' denotes that the proximity index in that row has the property designated in the column. On the basis of Properties 1–7 in Table X, we draw two main conclusions. First, the Jaffe measure, which has been the benchmark for empirical spillover research for almost two decades, is strictly dominated by the Mahalanobis measure. The Mahalanobis measure has the additional desirable property of allowing for between field overlap (BFO), which is important, as technology spillovers almost certainly occur across (as well as within) technology classes, for example, in biomedical engineering. Indeed, we find empirically that the Mahalanobis metric outperforms the Jaffe measure.

Second, no proximity index dominates every other measure. In particular, while the Mahalanobis measure dominates the Jaffe measure because of its ability to allow for between field overlap, it is not invariant with respect to non-overlapping fields (NOF), which the Exposure measure is. The conclusion that no single index dominates in terms of these properties is important, and

TABLE X

DESIRABLE PROPERTIES OF DISTANCE MEASURES

Name	Definition of $TECH_{ij}$	Economic Microfoundations *EMF*	Invariance to Re-Scaling *SCALE*	Within-Field Overlap *WFO*	Between-Field Overlap *BFO*	Nonoverlapping Fields *NOF*	Invariance to Aggregation Over Non-Active Fields *AGG*	Robustness to Aggregation of Active Fields *ROB*
Jaffe	$\frac{F_i' F_j}{\sqrt{F_i}\sqrt{F_j}}$		X	X			X	X
Mahalanobis	$\frac{F_i' \Omega F_j}{\sqrt{F_i}\sqrt{F_j}}$		X	X	X		X	X
Jaffe-Covariance	$F_i' F_j$		X	X		X	X	
Exposure	$F_i' F_j n_i$	X	X[a]	X		X	X	
Ellison–Glaeser Co-agglomeration	$\frac{\sum_\tau (s_{\tau i} - x_\tau)(s_{\tau j} - x_\tau)}{1 - \sum_\tau x_\tau^2}$	X	X	X				

Notes: The table compares the desirable theoretical properties of distance metrics as discussed in Section 7. Note that in constructing *SPILLTECH*, the *TECH* measure is multiplied by the R&D stock of firm j and then summed across all j. F_i denotes the vector of the shares of firm i's patenting in different technology fields, and Ω is the Mahalanobis matrix summarizing the co-location of technology fields. An "X" denotes that the distance measure has the indicated property, whereas a blank indicates that it does not.

[a]Although the Exposure index does not satisfy *SCALE* in a levels specifications, it does satisfy *SCALE* in a log specification (as in this paper).

suggests that the choice for empirical researchers will turn on the weight they put on these properties, which, in turn, depends on their particular research question.

8. CONCLUSIONS

Firm performance is affected by two countervailing R&D spillovers: positive effects from technology spillovers and negative business stealing effects from R&D by product market rivals. We develop a general framework showing that technology and product market spillovers have testable implications for a range of performance indicators: market value, cite-weighted patents, productivity, and R&D and then exploit these using distinct measures of a firm's position in *technology* space and *product market* space. Using panel data on U.S. firms over a 20-year period, we show that both technology and product market spillovers operate, but, despite the business stealing effect, we calculate that the social rate of return is much larger than the private return. At the aggregate level, this implies under-investment in R&D, with the socially optimal level being between two and three times as high as the privately optimal level of R&D. Our findings are robust to alternative definitions of the distance metric (including our new Mahalanobis measure) and the use of R&D tax credits to provide exogenous variation in R&D expenditure.

Using the model and the parameter estimates, we find that the social returns to R&D performed by smaller firms are lower than the social return to R&D performed by larger firms. This is essentially because smaller firms tend to operate more in technological "niches"—being less connected to other firms in technology space, they generate smaller positive spillovers. This finding suggests that R&D policies tilted toward smaller firms may be unwise if the objective is to redress market failures associated with technology spillovers. Of course, there may be other reasons to support smaller firms, such as liquidity constraints or perhaps a lesser capacity to appropriate the returns from their own R&D.

There are various extensions to this line of research. First, we make some inroads into industry heterogeneity by examining three high-tech sectors, but much more could be done within our framework to study how technology spillovers and business stealing vary across sectors, and the factors that determine them. Second, it is possible to exploit more detailed industry-specific data sets to study this phenomenon in the context of a more explicit structural model. Third, it would be interesting to investigate in greater detail how other mechanisms of knowledge transfer potentially shape both technology and product market spillovers, such as trade (e.g., Keller (1998, 2009)), supply chains, and personnel movements (e.g., Stoyanov and Zubanov (2012)). Finally, we have confined our analysis to the United States, but there is no reason why the same techniques cannot be extended to examine geographical areas outside the U.S. (using other nations' technological policies to generate quasi-exogenous variation in the R&D tax price).

Despite the need for these extensions, we believe that the methodology offered in this paper offers a fruitful way to analyze the existence of these two distinct types of R&D spillovers that are much discussed in the growth, productivity, and industrial organization literature, but are rarely subjected to rigorous empirical testing.

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