Identifying technology spillovers and product market rivalry*

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Abstract

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 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.

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1. Introduction

Research and development (R&D) spillovers have been a major topic in the growth, productivity and industrial organization literatures for many decades. Theoretical studies have explored the impact of R&D on the strategic interaction among firms and long run growth.[1] While many empirical studies appear to support the presence of technology spillovers, there remains a major problem at the heart of the literature. This arises from the fact that R&D generates at least two distinct types of "spillover" effects. The first is *technology* (or knowledge) *spillovers* which may increase the productivity of other firms that operate in similar technology areas. 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 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 in order to asses 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-

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

digit industries. This allows us to construct distinct measures of the distance between firms in the technology and product market dimensions.[2] We show that the significant variation in these two dimensions allows us to distinguish empirically between technology and product market spillovers.[3] 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 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 the paper is distinguishing a spillover interpretation from the possibility that positive interactions are just a reflection of spatially correlated technological 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 which may be erroneously picked up by a spillover measure. This issue is an example of the classic "reflection problem" discussed by Manski (1991). 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

[2] 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, Bransetter and Sakakibara (2002) make an important contribution by empirically examining the effects of technology closeness and product market overlap on patenting in Japanese research consortia.

[3] 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 compete in the PC market and only Intel and Motorola compete in the semi-conductor market, with little product market competition between the two pairs. Appendix D has more details on this and other examples.

"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 weighted 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.[4]

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 $SPILLTECH_i = \Sigma_{j \neq i} w_{ij} G_j$ 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 multi-dimensional 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 seek to 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.[5]

While we use the Jaffe measure of distance as the baseline specification, we also extend the

[4] 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 et al. 2007). Other approaches include using international data and weighting domestic and foreign R&D stocks by measures including imports, exports and FDI (see, for example, Coe et al. 2008).

[5] 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 et al. 1993), which we investigate in Section 6.

empirical analysis by estimating the model with a number of alternatives. Most important, 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 micro-foundations 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. A series of web Appendices contain 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).

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.[6] We study a two-stage game. In stage 1 firms decide their R&D spending and this produces knowledge that is taken as pre-determined 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 stocks in the reduced form profit function.

[6] This approach has some similarities to Jones and Williams (1998, 2000) who examine an endogeneous growth model with business stealing, knowledge spillovers and congestion externalities. Their focus, however, is 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) social returns to R&D are about two to four times greater than private returns.

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 contains several extensions to the basic model. Firstly, we allow firms to overlap simultaneously in product market and technology space and also allow for more than three firms in the economy. Secondly, we consider a tournament model of R&D (rather than the non-tournament model which is the focus of this section). Thirdly, we allow patenting to be endogenously chosen by firms rather than only as an indicator of knowledge, k. The predictions of the model are shown to be generally robust to all these extensions.[7]

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 example, if k_0 increases the demand for firm 0 (e.g. product innovation), its profits would increase for any given level of price or output in the second stage.[8]

The best response 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 $f(.)$ 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 do 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.[9]

Stage 1. Firm 0 produces innovations with its own R&D, possibly benefiting from

[7] In sub-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).

[8] 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.

[9] 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.

spillovers from firms that it is close to 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 $\phi(.)$ 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 $\phi(.)$ is common to all firms. Firm 0 solves the following problem:

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

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.[10] Comparative statics yield

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

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 $\Pi_{12} > 0$ – i.e., if k_0 and k_m are strategic complements (respectively, substitutes).[11] We also obtain:

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

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

[11] 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 et al., 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).

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

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:

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

We now discuss the intuition for the basic predictions of the model, which are summarized in Table 1. 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 1). 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 has no effect on the firm's production of knowledge and thus no direct effect on patenting or TFP (see equation (2.6)). Thirdly, 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 – i.e. it depends on the sign of Π_{12} (see equation (2.4)). As expected, R&D reaction functions slope upwards if k_0 and k_m are strategic complements and downwards 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 – i.e. 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.[12] 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)).

[12] 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.

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, 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).[13] It turns out 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 be negatively correlated with productivity because it will depress firm 0's prices and therefore measured "revenue" productivity.

Three points about identification from Table 1 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.[14]

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 dataset and how we move from the discrete indicator of proximity in the theory section to a continuous empirical metric. Appendix B provides details on the data, with the data and estimation files to replicate all results available on-line.[15]

3.1. Modelling Technological Proximity Measures

Technological proximity measures are rarely given a clear micro-economic foundation or statistical justification. In Section 7 we consider more formally the desirable properties of spillover

[13] 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 behaviour, see Hall and Ziedonis (2001), and Noel and Schankerman (2006).

[14] 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.

[15] http://www.stanford.edu/~nbloom/BSV.zip

measures. In this section we provide some micro-foundations 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 $\tau \in (1, \Upsilon)$ technology classes (or "fields"), and we take this allocation as the exogenous technological profile of the firm (we consider the endogenous allocation of R&D efforts across fields in sub-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 $n_i = \sum_{\tau=1}^{\Upsilon} n_{i\tau}$). 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 sub-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 from firm j to firm i is therefore:

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

Define the 1xΥ vector $F_i = (F_{i1}, ..., F_{i\Upsilon})$ where $F_{i\tau} = \frac{n_{i\tau}}{n_i}$ and similarly for $F_j = (F_{j1}, ..., F_{j\Upsilon})$.

[16] A related approach has been developed in the sociology literature to measure ethnic segregation. Lieberson (1981) proposes 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.

We define the "exposure" measure of technological proximity between two firms as $TECH_{ij}^{E} = F_i F_j' n_i$ and the technology spillover "pool" for firm i as:

$$SPILLTECH_i^E = \omega \sum_{j \neq i} TECH_{ij}^{E} n_j \tag{3.2}$$

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, $TECH_{ij}^{J-COV}$ and define the corresponding spillover measure $SPILLTECH_i^{J-COV} = \omega \sum_{j \neq i} TECH_{ij}^{J-COV} n_j$. Note that $TECH_{ij}^{E} = n_i TECH_{ij}^{J-COV}$ so $SPILLTECH_i^{E} = n_i SPILLTECH_i^{J-COV}$. 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, $TECH_{ij}^{J} = \frac{F_i F_j'}{(F_i F_i')^{\frac{1}{2}} (F_j F_j')^{\frac{1}{2}}}$, normalizes the uncentered covariance in $TECH_{ij}^{J-COV}$ 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: i.e. $F_i F_i'$ will increase, but so will $(F_i F_i')^{\frac{1}{2}} (F_j F_j')^{\frac{1}{2}}$. 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 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 will discuss the properties of many different measures of proximity in relation to some *ex ante* desirable features of proximity indices. We also show *ex post* the robustness of our results to many alternative distance metrics in the results section.

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 section, 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 $\Upsilon x \Upsilon$ 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

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

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

$$SPILLTECH_i^{EM} = \sum_{j \neq i} TECH_{ij}^{EM} n_{j.} = \sum_{j \neq i} F_i \Omega F_j^{'} n_{i.} n_{j.} \tag{3.4}$$

3.3. Extension to Product Market Proximity

With suitable reinterpretation, the preceding micro-foundations 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 'tilda' to denote variables for product market closeness, e.g. $\tilde{n}_{iq}$ rather than n_{iq}. We define the vector $\tilde{F}_i = (\tilde{F}_{i1}, ..., \tilde{F}_{i\Upsilon})$, 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, $SIC_{ij}^E = \tilde{F}_i \tilde{F}_j^{'} \tilde{n}_i$, and the product market spillover "pool" for firm i:

$$SPILLSIC_i^E = \tilde{\omega} \sum_{j \neq i} SIC_{ij}^E \tilde{n}_j \tag{3.5}$$

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

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.

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). This contains 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 which 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

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

[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 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)

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 $T_i = (T_{i1}, T_{i2}, ...T_{i426})$, 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 sub-section 3.1. As noted above, our basic technology closeness measure is calculated as the uncentered correlation between all firm i, j pairings, following Jaffe (1986):

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

For notational simplicity, in what follows we simply denote this as $TECH_{ij}$ (rather than $TECH_{ij}^J$). This index ranges between zero and one, 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

$$SPILLTECH_{it} = \Sigma_{j \neq i} TECH_{ij} G_{jt}. \tag{3.7}$$

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 sub-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 $S_i = (S_{i1}, S_{i2}, ...S_{i597})$, where S_{ik} is the share of sales

[20] The main results pool the patent data across the entire sample period, but we also experimented with sub-samples. 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.

of firm i in the four digit industry k.[21] S_i is the empirical counterpart to $\widetilde{F}_i$ in sub-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:

$$SIC_{i,j} = \frac{(S_i S_j')}{(S_i S_i')^{1/2}(S_j S_j')^{1/2}} \tag{3.8}$$

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

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

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 micro-foundations to proximity measures, where we developed an (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 that 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, $SPILLTECH^M$, is notationally quite involved so it presented in Appendix C.2. A similar distance measure can also be constructed for the distance between firms in product market space, which we call $SPILLSIC^M$. We present results based on both the Jaffe and Mahalanobis distance metrics in the empirical section.

3.8. Some Issues with the Dataset

Although the Compustat/NBER database is the best publicly available dataset to implement our framework, there are issues with using it. First, the finance literature has debated the

[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).

extent to which the breakdown of firm sales into four digit industries from the Compustat Segment Dataset is reliable.[22] We examine this problem using BVD, an alternative firm-level database to calculate product market closeness in sub-section 6.3.2. Second, Thompson and Fox-Kean (2005) have argued that the three-digit patent classification may be too crude, so we will examine the more disaggregated patent sub-class data they use in sub-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 dataset covers the bulk of reported R&D in the U.S. economy. Further, we do not drop firms that exit or those that only operate in one line of business. Sample selection issues are discussed in more detail in Appendix B.4.

3.9. Descriptive Statistics of $SPILLTECH$ and $SPILLSIC$

In order 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 $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$ is 0.422. For estimation in logarithms with fixed effects and time dummies the relevant correlation in the change of $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$ 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 across the unit box rather than a few outliers. Finally, in Appendix D 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.

Table 2 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.

[22] For example, Villalonga (2004) argues 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 finds no discount in manufacturing. Since our sample is manufacturing focused, (81% of our R&D is in manufacturing), this issue is less problematic here.

4. Econometrics

In the theory discussion summarized in Table 1 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 non-linear 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 the 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, but we sketch the strategy here. The Hall-Jorgenson user cost of capital for firm i, ρ_{it}^U, is

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

where D_{it} is the discounted value of tax credits and depreciation allowances, τ_{st} (shorthand for τ_{s_it}) is the rate of corporation tax (which has a state as well as a Federal component), I_t is the real interest rate, δ the depreciation rate of R&D capital and $\frac{\Delta p_t}{p_{t-1}}$ is the growth of the

[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.

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, $\rho^P_{it} = \frac{(1-D_{it})}{(1-\tau_{st})}$.

Values of ρ^P_{it} of unity are equivalent to R&D tax neutrality, while values below unity denote net tax incentives for R&D. ρ^P_{it} will vary across firms for 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 (2008) 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.

Thirdly, 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:

$$\ln\left(\frac{V}{A}\right)_{it} = \ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it}\right)+\gamma_2 \ln SPILLTECH_{it}+\gamma_3 \ln SPILLSIC_{it}+\gamma_4 X^V_{it}+\eta^V_i+\tau^V_t+\upsilon^V_{it} \tag{4.3}$$

[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 onwards 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.

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 $\gamma_1(G/A)$ were "small" we could approximate $\ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it}\right)$ by $\gamma_1\left(\frac{G}{A}\right)_{it}$, but this will not be a good approximation for many high tech firms, so we approximate $\ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it}\right)$ 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:

$$\begin{aligned}\ln(V/A)_{it} &= \phi((G/A)_{it-1}) + \gamma_2 \ln SPILLTECH_{it-1} + \gamma_3 \ln SPILLSIC_{it-1} \\ &\quad + \gamma_4 X_{it}^V + \eta_i^V + \tau_t^V + \upsilon_{it}^V \qquad (4.4)\end{aligned}$$

4.3. Patent Equation

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

$$P_{it} = \exp(\lambda_1 \ln G_{it-1} + \lambda_2 \ln SPILLTECH_{it-1} + \lambda_3 \ln SPILLSIC_{it-1} + \lambda_4 X_{it}^P + \eta_i^P + \tau_t^P + \upsilon_{it}^P) \qquad (4.5)$$

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):

$$\ln Y_{it} = \varphi_1 \ln G_{it-1} + \varphi_2 \ln SPILLTECH_{it-1} + \varphi_3 \ln SPILLSIC_{it-1} + \varphi_4 X_{it}^Y + \eta_i^Y + \tau_t^Y + \upsilon_{it}^Y \qquad (4.6)$$

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

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 marginal effects of $SPILLTECH$ and $SPILLSIC$ in equation (4.6) would be qualitatively the same as that 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 towards dealing with the problem of firm-specific prices, and we show that the negative coefficient on $SPILLSIC$ becomes essentially zero once we control for these additional factors.

4.5. R&D equation

We write the R&D intensity equation as:

$$\ln(R/Y)_{it} = \alpha_2 \ln SPILLTECH_{it-1} + \alpha_3 \ln SPILLSIC_{it-1} + \alpha_4 X_{it}^{R} + \eta_i^{R} + \tau_t^{R} + \upsilon_{it}^{R} \quad (4.7)$$

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 3 summarizes the results for the market value equation. In this 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]

[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 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

These are both 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 towards zero is illustrated for $SPILLSIC$ - if we failed to control for technology spillovers we would find 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 A2 and shows that the excluded instruments are strong. The second stage coefficients on the spillover terms in column (6) of Table 3 are correctly signed and significant with absolute magnitudes larger than the baseline column (2).

5.2. Patent Equation

Table 4 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

since G/A is not "small" - the mean is close to 50% (see Table 2). 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 vs. fixed effects (p-value = 0.02).

[31] We also tried an alternative specification that introduces current (not lagged) values of the two spillover measures, and estimate 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*).

and statistically insignificant coefficient.

In column (2) we control for firm fixed effects by using the Blundell et al (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 3, 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]The coefficient on $SPILLSIC$ is statistically insignificant and much smaller than $SPILLTECH$ throughout Table 4, which is consistent with our basic model.

5.3. Productivity Equation

Table 5 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 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).

[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 et al (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 et al (1999) method.

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 6 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 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 6, 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 6 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

[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 lead 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*).

[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 6 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.

driven by common shocks.

5.5. Summary of basic empirical results

Table 7 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]

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 in order 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 will define 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 where co-located or co-agglomerated in the same geographic areas. We will discuss geographical concerns explicitly in the next sub-section, but since in our basic model we focused only on closeness in technology and product markets, we continue to do so in this sub-section. In the

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

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 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 centre it at the mean of the 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 8 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. 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 3).

Overall then, the alternative more 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-US based inventors. For each firm we then define the vector $L_i^T = (L_{i1}^T, L_{i2}^T, ...L_{i136}^T)$, where $L_{i\tau}^T$ is the share of patents of firm i in location g, which runs from 1 to 136 reflecting the 50 different US states and 86 foreign countries across which we observe the distribution of patents. The geographical technological closeness measure, $GEOG_{ij}^T$ $(i \neq j)$, is calculated as the uncentered correlation between all firm i, j pairings:

$$GEOG_{ij}^T = \frac{(L_i^T L_j^{T'})}{(L_i^T L_i^{T'})^{1/2}(L_j^T L_j^{T'})^{1/2}} \tag{6.2}$$

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 this data we can define a vector of a firm's location of sales, $L_i^S = (L_{i1}^S, L_{i2}^S, ...L_{i9}^S)$, and a geographical sales closeness measure, $GEOG_{ij}^S$ $(i \neq j)$:

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

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

$$\begin{aligned} SPILLTECH_{it}^{GEOG} &= \Sigma_{,j\neq i} TECH_{ij} \times GEOG_{ij}^T \times G_{jt} \\ SPILLSIC_{it}^{GEOG} &= \Sigma_{j\neq i} SIC_{ij} \times GEOG_{ij}^S \times G_{jt} \end{aligned} \tag{6.4}$$

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 distances is unimportant for spillovers then the basic measure should dominate.

Panel C of Table 8 reports the results. In the first three columns the coefficient on geographically weighted technology spillovers ($SPILLTECH_{it}^{GEOG}$) 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 et. al. (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 US firms) operate in mainly quite globalized product market where physical distance is relatively unimportant.[40]

6.3. Other Alternative distance measures

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

6.3.1. Jaffe-Covariance and Exposure based Measures of spillovers

In sub-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 labelled the Jaffe-Covariance and Exposure measures. Although closer to the formal model, these measure had some statistically unattractive properties such as lack of robustness to arbitrary aggregations of technology classes, which is why we preferred the conventional Jaffe measure as our baseline. Panel D of Table 8 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 sub-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

[40] Of course, given the coarseness of our measure of product-market geography another interpretation is our geographic market closeness measure is too noisy to get a significant interaction. This is certainly possible, although 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 from firm pairs for which firms are either close in technology space or product space but not both. Doing this we find that first $TECH$ 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 A3 Panel D).

are quite stable illustrating that it is the numerator of the distance metric which 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 A3 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 Dataset

The finance literature has debated the extent to which the breakdown of firm sales into four digit industries from the Compustat Segment Dataset 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 Dataset measures is high (e.g. within-firm correlation of $\ln(SPILLSIC)$ is 0.737). The empirical results (Panel B in Table A3) 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 a finer disaggregation is better for measuring spillovers. As Henderson, Jaffe and Trajtenberg (2005) point 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 A3).

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 dataset. Nevertheless, it would be worrying if the basic theory was contradicted in the high-tech sectors, as this would

[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.

suggest our results might be due to biases induced by pooling across heterogenous 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 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 magnitude 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 sub-section we use our coefficient estimates to calculate the private and social rates of return to R&D for the whole sample and for different sub-groups 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 which 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 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 provides a detailed discussion of how to calculate these rates of return for individual firms within our analytical framework. In the general case,

[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).

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 formulae to compute the returns presented in this sub-section, 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:

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

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 and the indirect effect it has by augmenting the stock of technology spillovers enjoyed by all other firms. The MSR is larger the stronger is the impact of the technology spillovers generated by the firm (φ_2).

In this special case, the marginal private return can be expressed as:

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

In equation (6.6) γ_3 is the coefficient on $SPILLSIC$ in the market value equation. 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]

[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.

[45] We need an assumption on the parameter σ in order to back out the implied output redistribution from

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 $|\sigma\gamma_3|$. In the general case, 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 either 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% (= $2.48 * (0.043 + 0.191)$, and an estimate of the MPR of 20.8% (= $2.48 * (0.043 + 0.042)$). This calculation shows that, for the sample of firms taken together, the marginal social returns are between two to three times the private returns, indicating under-investment in R&D. We can use our estimates of the private and social returns to infer the gap between the observed and socially optimal level of R&D. To do this we need an assumption about the price 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 9. 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

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 over-estimate the private return and thus under-estimate the wedge between private and social returns to R&D.

[46] Our estimated coefficients on the tax credit variables from the first stage IV regression (column (3), Table A2), 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) find a long-run value of -1.1 estimating using cross-country and time variation in R&D tax credits and report similar values of around unity for other papers in the literature.

Table 9 shows the results from using the Mahalanobis 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 shows 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, i.e. to net out appropriate R&D depreciation. One approach is to assume 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) argue, 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.

Second, in rows 4-7 we split firms by their quartiles of size. We find that larger firms have a *larger 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 who 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, suggests 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

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

of our main empirical findings, 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 micro-foundation. This property is self-evidently desirable.

2. *SCALE*: The index is invariant (up to a proportionality factor) to re-scaling 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

[48] There is a related approach in the sociology literature on segregation measures. In an influential paper, Massey and Denton (1986) identify five dimensions of (geographic) segregation, relate the various existing measures of segregation in the sociology literature to these different dimensions, and then construct a synthetic measure using factor analysis. The five dimensions are: eveness, exposure, concentration, centralisation, 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 sub-section 6.1 and Appendix E. Exposure relates to the probability that different members of distinct groups (firms in our context) come into contact with each other, which we developed in sub-sections 3.1-3.3.

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 B_2 denote 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 j does R&D. Property 6 states that, if neither firm i nor 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 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 $TECH_{ij}(B_1, B_2)$ 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 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 sub-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 $\mid \frac{TECH_{ij}(B_2)}{TECH_{ij}(B_1)} - 1 \mid$.

In Table 10 we compare five proximity measures: (1) the standard Jaffe index, (2) Mahalanobis generalization of the Jaffe index, (3) Jaffe covariance index, (4) Exposure index and (5) Ellison-Glaeser co-agglomeration 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 10 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 out-performs 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 suggests 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, 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 twenty 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 the private return. At the aggregate level this implies under-investment in R&D, with the socially optimal level being between two to three times as high as the observed 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 return to R&D by smaller firms is lower for larger firms, 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 towards 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 examined three high-tech, 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 datasets to study this phenomenon in the context of a more explicit structural model. Thirdly, 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).

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 is rarely subjected to rigorous empirical testing.

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Appendices

Given the large number of appendices, there is an unusually heavy demand on mathematical notation in this paper. As a guide for the reader, we follow three rules. First, within the body of the text, we use a consistent set of symbols. Second, when the text draws from an appendix, we ensure that the notation is the same in that appendix and the text. Third, within each appendix we use a consistent set of notation. However, some of the same symbols may be used in different appendices, subject to the constraint imposed by the second rule.

A. Generalizations of the Theoretical Model

In this Appendix we describe three generalizations of the simple model presented in Section 2. First, we allow for a more general form of interaction between firms in technology and product market space (where there can be overlap) and also consider the N-firm case (rather than three firm case). Second, we examine tournament models of R&D (rather than the non-tournament model in the baseline case). We show, with light modifications, that the essential insights of our simply model carry through to these more complex settings. Third, we allow the patenting decision to be an endogenous choice for the firm (rather than simply having patents as simply an empirical indicator of successfully produced knowledge from R&D). Although our main model predictions are robust, the extension to endogenous patenting implies that the partial derivative of patenting with respect to product market rivals' R&D ($SPILLSIC$) will be non-zero (it is zero in the basic model).

A.1. General form of interactions in technology and product market space

We begin with the general expression for flow profit

$$\pi^i = \pi^*(r_i, r_{-i}) \tag{A.1}$$

where r_{-i} is the vector of R&D for all firms other than i. In this formulation, the elements of r_{-i} captures both technology and product market spillover effects. To separate these components, we assume that (A.1) can be expressed as

$$\pi^i = \pi(r_i, r_{i\tau}, r_{im}) \tag{A.2}$$

where

$$r_{i_\tau} = \sum_{j \neq i} TECH_{ij} r_{ij} \tag{A.3}$$

$$r_{im} = \sum_{j \neq i} SIC_{ij} r_{ij} \tag{A.4}$$

and the partial derivatives are $\pi_1 > 0, \pi_2 \geq 0, \pi_3 \leq 0, \pi_{12} \gtrless 0, \pi_{13} \gtrless 0,$and $\pi_{23} \gtrless 0.$The technology spillover effect is $\pi_2 \geq 0$, and the business stealing effect is $\pi_3 \leq 0$. We do not constrain the effect of technology and product market spillovers on the marginal profitability of own R&D. Note that own R&D and product market spillovers are strategic substitutes if $\pi_{13} < 0$ and strategic complements if $\pi_{13} > 0$.

Equation (A.2) imposes constraints on (A.1) by partitioning the total effect of the R&D by each firm $j \neq i$ into technology spillovers $r_{i\tau}$ and product market rivalry spillovers r_{im} and by assuming that the marginal contribution of firm j to each pool is proportional to its 'distance' in technology and product market space, as summarized by $TECH_{ij}$ and SIC_{ij} (i.e. we assume that $\frac{\partial \pi^*}{\partial r_j}$can be summarized in the form $\pi_2^i TECH_{ij} + \pi_3^i SIC_{ij}$ for each $j \neq i$).

Firm i chooses R&D to maximize net value

$$\max_{r_i} V^i = \pi(r_i, r_{i\tau}, r_{im}) - r_i$$

Optimal R&D r_i^* satisfies the first order condition

$$\pi_1(r_i^*, r_{i\tau}, r_{im}) - 1 = 0 \tag{A.5}$$

We want to study how (exogenous) variations in $r_{i\tau,}$ and r_{im} affect optimal R&D. To do this we choose an arbitrary subset of firms, S, and make compensating changes in their R&D such that either r_{im} or $r_{i\tau}$ is held constant. This allows to to isolate the impact of the spillover pool we are interested in. Consider a subset of firms denoted by $s \in S$ where $s \neq i$, and a set of changes in their R&D levels, $\{dr_s\}$ that satisfy the constraint $dr_{im} = \sum_{s \in S} SIC_{is} dr_s = 0$. These changes imply some change in the technology spillovers $dr_{i\tau} = \sum\limits_{s \in S} TECH_{is} dr_s$, which in general will differ from zero (it can be either positive or negative depending on the $TECH$ and SIC weights). Now totally differentiate the first order condition, allowing only r_s for $s \in S$ to change.[49] This gives

$$\pi_{11} dr_i + \pi_{12} \sum_{s \in S} TECH_{is} dr_s + \pi_{13} \sum_{s \in S} SIC_{is} dr_s = 0$$

But the third summation is zero by construction ($dr_{im} = 0$), and the second summation is just $dr_{i\tau}$. So we get

$$\frac{\partial r_i^*}{\partial r_{i\tau}} = -\frac{\pi_{12}}{\pi_{11}} \tag{A.6}$$

By similar derivation we obtain

$$\frac{\partial r_i^*}{\partial r_{im}} = -\frac{\pi_{13}}{\pi_{11}} \tag{A.7}$$

Equation (A.6) says that if we make compensating changes in the R&D such that the pool of product market spillovers is constant, the effect of the resulting change in technology spillovers has the same sign as π_{12}.This can be either positive or negative depending on how technology spillovers affect the marginal productivity of own R&D. Equation (A.7) says that if we make compensating changes in the R&D such that the pool of technology spillovers is constant, the effect of the resulting change in product market spillovers has the same sign as $\pi_{13}-$ the sign depends on whether R&D by product market rivals is a strategic substitute or complement for the firm's own R&D.

[49] We assume that the changes in R&D do not violate the restriction $r_s \geq 0$.

Using the envelope theorem, the effects of $r_{i\tau}$ and r_{im} on the firm's market value are

$$\begin{aligned}\frac{\partial V_i}{\partial r_{i\tau}} &= \pi_2 \geq 0 \\ \frac{\partial V_i}{\partial r_{im}} &= \pi_3 \leq 0\end{aligned}$$

These equations say that an increase in technology spillovers raises the firm's market value, and an increase in product market rivals' R&D reduces it.

One remark is in order. There are multiple (infinite) different ways to change R&D in a subset of firms so as to ensure the constraint $dr_{im} = 0$ is satisfied. Each of the combinations $\{dr_s\}$ that do this will imply a different value of $dr_{i\tau} = \sum_{s\in S} TECH_{is} dr_s$. Thus the discrete impact of such changes will depend on the precise combination of changes made, but the marginal impact of a change in $dr_{i\tau}$ does not depend on that choice.

A.2. Tournament Model of R&D Competition with Technology Spillovers

In this sub-section we analyze a stochastic patent race model with spillovers. We do not distinguish between competing firms in the technology and product markets because the distinction does not make sense in a simple patent race (where the winner alone gets profit). For generality we assume that n firms compete for the patent.

Stage 2

Firm 0 has profit function $\pi(k_0, x_0, x_m)$. As before we allow innovation output k_0 to have a direct effect on profits, as well as an indirect (strategic) effect working through x. In stage 1, n firms compete in a patent race (i.e. there are $n-1$ firms in the set m). If firm 0 wins the patent, $k_0 = 1$, otherwise $k_0 = 0$. The best response function is given by $x_0^* = \arg\max \pi(x_0, x_m, k_m)$. Thus second stage profit for firm 0, if it wins the patent race, is $\pi(x_0^*, x_m^*; k_0 = 1)$, otherwise it is $\pi(x_0^*, x_m^*; k_0 = 0)$.

We can write the second stage Nash decision for firm 0 as $x_0^* = f(k_0, k_m)$ and first stage profit as $\Pi(k_0, k_m) = \pi(k_0, x_0^*, x_m^*)$. If there is no strategic interaction in the product market, π^i does not vary with x_j and thus x_i^* and Π^i do not depend directly on k_j.Recall that in the context of a patent race, however, only one firm gets the patent: if $k_j = 1$, then $k_i = 0$. Thus Π^i depends indirectly on k_j in this sense. The patent race corresponds to an (extreme) example where $\partial\Pi^i(k_i, k_j)/\partial k_j < 0$.

Stage 1

We consider a symmetric patent race between n firms with a fixed prize (patent value) $\Delta = \pi^0(f(1,0), f(0,1); k_0 = 1) - \pi^0(f(0,1), f(1,0); k_0 = 0)$. The expected value of firm 1 can be expressed as

$$V^0(r_0, r_m) = \frac{h(r_0, (n-1)r_m)\Delta - r_0}{h(r_0, (n-1)r_m) + (n-1)h(r_m, (n-1)r_m + r_0) + R}$$

where R is the interest rate, r_m is the R&D spending of each of firm $0's$ rivals, and $h(r_0, r_m)$ is the probability that firm 0 gets the patent at each point of time given that it has not done so before (hazard rate). We assume that $h(r_0, r_m)$ is increasing and concave in both arguments. It is rising in r_m because of spillovers. We also assume that $h\Delta - R \geq 0$ (expected benefits per period exceed the opportunity cost of funds).

The best response is $r_0^* = \arg\max V^0(r_0, r_m)$.Using the shorthand $h^0 = h(r_0, (n-1)r_m)$ and subscripts on h to denote partial derivatives, the first order condition for firm 0 is

$$(h_1\Delta - 1)\{h^0 + (n-1)h^m + R\} - (h^0\Delta - r_1)\{h_1^0 + (n-1)h_2^m\} = 0$$

Imposing symmetry and using comparative statics, we obtain

$$\begin{aligned} sign\left(\frac{\partial r_0}{\partial r_m}\right) &= sign\{h_{12}(h\Delta(n-1) + r\Delta - R\} + \{h_1(n-1)(h_1\Delta - 1)\} \\ &\quad -\{h_{22}(n-1)(h\Delta - R)\} - h_2\{(n-1)h_2\Delta - 1\}\} \end{aligned}$$

We assume $h_{12} \geq 0$ (spillovers do not reduce the marginal product of a firm's R&D) and $h_1\Delta - 1 \geq 0$ (expected net benefit of own R&D is non-negative). These assumptions imply that the first three bracketed terms are positive. Thus a sufficient condition for strategic complementarity in the R&D game ($\frac{\partial r_0}{\partial r_m} > 0$) is that $(n-1)h_2\Delta - 1 \leq 0$. This requires that spillovers not be 'too large'. If firm 0 increases R&D by one unit, this raises the probability that one of its rivals wins the patent race by $(n-1)h_2$. The condition says that the expected gain for its rivals must be less than the marginal R&D cost to firm 0.

Using the envelope theorem, we get $\frac{\partial V^0}{\partial r_m} < 0$. The intuition is that a rise in r_m increases the probability that firm m wins the patent. While it may also generate spillovers that raise the win probability for firm 0, we assume that the direct effect is larger than the spillover effect. For the same reason, $\frac{\partial V^0}{\partial k_m} = 0$. As in the non-tournament case, $\frac{\partial r_0}{\partial r_m} > 0$ and $\frac{\partial V^0}{\partial r_m} < 0$.The difference is that with a simple patent race, $\frac{\partial V^0}{\partial k_m}$ is zero rather than negative because firms only race for a single patent.[50]

A.3. Endogenizing the decision to patent

We generalize the basic non-tournament model to include an endogenous decision to patent. We study a two-stage game. In stage 1 firms make *two* decisions: (1) the level of R&D spending and (2) the 'propensity to patent'. The firm produces knowledge with its own R&D and the R&D by technology rivals. The firm also chooses the fraction of this knowledge that it protects by patenting. Let $\rho \in [0,1]$ denote this patent propensity and $\lambda \geq 1$ denote patent effectiveness – i.e. the rents earned from a given innovation if it is patented relative to the rents if it is not patented. Thus $\lambda - 1$ represents the patent premium and θk is the rent associated with knowledge k, where $\theta = \rho\lambda + (1-\rho)$. There is a fixed cost of patenting each unit of knowledge, c.

As in the basic model at stage 2, firms compete in some variable, x, conditional on their knowledge levels k. There are three firms, labelled 0, τ and m. Firms 0 and τ interact only in technology space but not in the product market; firms 0 and m compete only in the product market.

Stage 2

Firm $0's$ profit function is $\pi(x_0, x_m, \theta_0 k_0)$. 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.

The best response for firms 0 and m are given by $x_0^* = \arg\max \pi(x_0, x_m, \theta_0 k_0)$ and $x_m^* = \arg\max \pi(x_m, x_0, \theta_m k_m)$, respectively. Solving for second stage Nash decisions yields $x_0^* =$

[50] In this analysis we have assumed that $k = 0$ initially, so ex post the winner has $k = 1$ and the losers $k = 0$. The same qualitiative results hold if we allow for positive initial k.

$f(\theta_0 k_0, \theta_m k_m)$ and $x_m^* = f(\theta_m k_m, \theta_0 k_0)$. First stage profit for firm 0 is $\Pi(\theta_0 k_0, \theta_m k_m) = \pi(\theta_0 k_0, x_0^*, x_m^*)$, and similarly for firm m. If there is no strategic interaction in the product market, $\pi(\theta_0 k_0, x_0^*, x_m^*)$ does not vary with x_m and thus Π^0 do not depend on $\theta_m k_m$. We assume that $\Pi(\theta_0 k_0, \theta_m k_m)$ is increasing in $\theta_0 k_0$, decreasing in $\theta_m k_m$ and concave.

Stage 1

Firm $0's$ knowledge production function remains as

$$k_0 = \phi(r_0, r_\tau) \tag{A.8}$$

where we assume that $\phi(.)$ is non-decreasing and concave in both arguments and common to all firms. Firm 0 solves the following problem:

$$\max_{r_0, \rho_0} V^0 = \Pi(\theta_0 \phi(r_0, r_\tau), \theta_m k_m) - r_0 - c\rho_0 \phi(r_0, r_\tau) \tag{A.9}$$

The first order conditions are

$$r_0 \ : \ (\Pi_1^0 \theta_0 - c\rho_0)\phi_1^0 - 1 = 0 \tag{A.10}$$

$$\rho_0 \ : \ \Pi_1^0 \phi^0 (\lambda - 1) - c\phi^0 - 1 = 0 \tag{A.11}$$

where the subscripts denote partial derivatives and superscripts denote the firm. Comparative statics on equations (A.10) and (A.11) yield the following results for comparison with the baseline model:[51]

$$\frac{\partial r_0^*}{\partial r_\tau} = \frac{V_{\rho_0 \rho_0} V_{r_0 r_\tau} - V_{\rho_0 r_0} V_{\rho_0 \rho_\tau}}{-A} \gtrless 0 \tag{A.12}$$

where $V_{r_0 r_\tau} \equiv \frac{\partial^2 V}{\partial r_0 r_\tau}$,etc., and $A = V_{r_0 r_0} V_{\rho_0 \rho_0} - V_{r_0 \rho_0}^2 > 0$ by the second order conditions.

As in the basic model, the sign of $\frac{\partial r_0^*}{\partial r_\tau}$ depends on $sign$ $\{\phi_{12}\}$ and the magnitude of Π_{11}.We also obtain:

$$\frac{\partial r_0^*}{\partial r_m} = \frac{V_{\rho_0 \rho_0} V_{r_0 \rho_m} - V_{\rho_0 r_0} V_{\rho_0 \rho_m}}{-A} \gtrless 0 \text{ depending on } sign\{\Pi_{12}\} \tag{A.13}$$

$$\frac{\partial \rho_0^*}{\partial r_m} = \frac{V_{\rho_0 \rho_0} V_{r_0 r_m} - V_{\rho_0 r_0} V_{\rho_0 r_m}}{-A} \gtrless 0 \text{ depending on } sign\{\Pi_{12}\} \tag{A.14}$$

In signing the above results, we use the fact that $V_{r_0 r_0} < 0, V_{\rho_0 \rho_0} < 0, V_{\rho_0 r_0} > 0$ (provided Π_{11} is 'sufficiently small') and the other cross partials which are: $V_{r_0 r_\tau} = \frac{\phi_{12}}{\phi_1} + \theta_0^2 \phi_1^0 \phi_2^0 \Pi_{11}$; $V_{r_0 r_m} = \theta_0 \theta_m \phi_1^0 \phi_1^m \Pi_{12}$, $V_{r_0 \rho_\tau} = 0$; $V_{r_0 \rho_m} = (\lambda - 1)\theta_0 k_m \phi_1^0 \Pi_{12}$; $V_{\rho_0 r_\tau} = (\lambda - 1)\theta_0 k_0 \phi_2^0 \Pi_{11}$; $V_{\rho_0 r_m} = (\lambda - 1) k_0 \theta_m \phi_1^m \Pi_{12}$; $V_{\rho_0 \rho_\tau} = 0$; and $V_{\rho_0 \rho_m} = (\lambda - 1)^2 k_0 k_m \phi_2^0 \Pi_{12}$.

The basic results of the simpler model go through. First, an increase in technology spillovers (r_τ) has an ambiguous sign on own R&D spending, (equation (A.12)). Second, after some algebra we can show that $sign\{\frac{\partial r_0^*}{\partial r_m}\} = sign\{ \Pi_{12}\}$ provided that Π_{11} is 'sufficiently small'. An increase in product market rivals' R&D raises own R&D if they are strategic complements (conversely for strategic substitutes) [equation (A.13)]. Third, from the knowledge production function (A.8), it follows that technology spillovers raise firm $0's$ knowledge stock, $\frac{\partial k_0^*}{\partial r_\tau} \geq 0$, and product market rivals' R&D has no effect on it, $\frac{\partial k_0^*}{\partial r_m} = 0$. Finally, the impacts on the value

[51] This is not a full list of the comparative statics results.

of the firm follow immediately by applying the envelope theorem to the value equation (A.9): namely, $\frac{\partial V_0^*}{\partial r_\tau} \geq 0$ and$\frac{\partial V_0^*}{\partial r_m} \leq 0$.

The new result here is that an increase in the R&D by firm $0's$ product market rivals will affect the firm's propensity to patent, $\frac{\partial \rho_0^*}{\partial r_m}$ (equation (A.14). After some algebra, we can show that $sign\ \frac{\partial \rho_0^*}{\partial r_m} = sign \Pi_{12}$, provided that Π_{11} is 'sufficiently small'. Thus, if there is strategic complementarity ($\Pi_{12} > 0$), an increase in product market rivals' R&D raises the firm's propensity to patent (the opposite holds for strategic substitution). The intuition is that, under strategic complementarity, when rivals increase R&D spending (thus their stock of knowledge), this increases the marginal profitability of firm 0's R&D and thus the profitability of patenting (given the fixed cost of doing so). Thus R&D by product market rivals raises both R&D spending and patent propensity of firm 0.[52]

B. Data Appendix

B.1. The patents and Compustat databases

The NBER patents database provides detailed patenting and citation information for around 2,500 firms (as described in Hall, Jaffe and Trajtenberg (2005) and Jaffe and Trajtenberg, 2002). We started by using the NBER's match of the Compustat accounting data to the USPTO data between 1970 to 1999[53], and kept only patenting firms leaving a sample size of 1,865. These firms were then matched into the Compustat Segment ("line of business") Dataset keeping only the 795 firms with data on both sales by four digit industry and patents, although these need not be concurrent. For example, a firm which patented in 1985, 1988 and 1989, had Segment data from 1993 to 1997, and accounting data from 1980 to 1997 would be kept in our dataset for the period 1985 to 1997. The Compustat Segment Database allocates firm sales into four digit industries each year using firm's descriptions of their sales by lines of business. See Villalonga (2004) for a more detailed description.

Finally, this dataset was cleaned to remove accounting years with extremely large jumps in sales, employment or capital signalling merger and acquisition activity. When we removed a year we treat the firm as a new entity and give it a new identifier (and therefore a new fixed effect) even if the firm identifier (CUSIP reference) in Compustat remained the same. This is more general than including a full set of firm fixed effects as we are allowing the fixed effect to change over time. We also removed firms with less than four consecutive years of data. This left a final sample of 715 firms to estimate the model on with accounting data for at least some of the period 1980 to 2001 and patenting data for at least some of the period between 1970 and 1999. The panel is unbalanced as we keep new entrants and exiters in the sample.

The main variables we use are as follows (Compustat mnemonics are in parentheses). The book value of capital is the net stock of property, plant and equipment ($PPENT$) and employment is the number of employees (EMP). R&D (XRD) is used to create R&D capital stocks following inter alia Hall, Jaffe and Trajtenberg (2005). This uses a perpetual inventory method with a depreciation rate (δ) of 15%. 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 $\delta = 0.15$. For the first year we observe a firm we assume it is in steady state so $G_0 = R_0/(\delta + g)$. We use sales as our output measure ($SALE$) but also compare this with value added specifications. Industry

[52] Since product market rivals' R&D does not affect knowledge production by firm 0, this result for the propensity to patent also applies to the number of patents taken out by firm 0.

[53] We dropped pre-1970 data as being too outdated for our 1980s and 1990s accounts data.

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 ($MKVAF, PSTK, DT$ and ACT). The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles other than R&D ($PPENT, INVT, IVAEQ, IVAO$ and $INTAN$). Tobin's Q was winsorized by setting it to 0.1 for values below 0.1 and at 20 for values above 20 (see Jenny Lanjouw and Mark Schankerman, 2004).

B.2. Other variables

The construction of the spillover variables is described in Section 3 above in detail. About 80% of the variance of $SPILLTECH$ and $SPILLSIC$ is between firm and 20% is within firm. When we include fixed effects we are, of course, relying on the time series variation for identification. Industry sales were constructed from total sales of the Compustat database by four digit industry code and year, and merged to the firm level in our panel using each firm's distribution of sales across four digit industry codes.

B.3. Using the tax treatment of R&D to construct Instrumental Variables

B.3.1. Methodology

To fix ideas, consider our basic model for firm productivity and abstract away from all other variables except own R&D and the technology spillover term. Similar issues arise for the other three equations, subject to additional complications noted below.

$$\ln Y_{it} = \beta_1 \ln(\Sigma_{j \neq i} TECH_{ij} R_{jt-1}) + u_{it} \tag{B.1}$$

We are concerned that $E[u_{it} \ln(\Sigma_{j \neq i} TECH_{ij} R_{jt-1})] \neq 0$, so OLS is inconsistent, and consider instrumental variable techniques. Note that R&D spillovers are entered lagged at least one period and that fixed effects and other covariates are also included. Given these considerations, the existing literature has argued that the bias on a weakly exogenous variable is likely to be small.

We consider two candidate instrumental variables (z) based on R&D-specific supply side shocks: firm and state-wide R&D tax credits. The Hall-Jorgenson user cost of capital for firm i, ρ_{it}^U is

$$\rho_{it}^U = \frac{(1 - D_{it})}{(1 - \tau_{st})}[I_t + \delta - \frac{\Delta p_t}{p_{t-1}}] \tag{B.2}$$

where D_{it} is the discounted value of tax credits and depreciation allowances, τ_{st} (which is 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 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, $\rho_{it}^P = \frac{(1-D_{it})}{(1-\tau_{st})}$.

We decompose the variation of ρ_{it}^P into two broad channels: "firm-level", ρ_{it}^F, based on firm-level interactions with the Federal tax rules, and "State level" ρ_{it}^S. We use the State by year R&D tax-price data from Wilson (2009) who quantifies the impact of State-level tax credits, depreciation allowances and corporation taxes. The firms in our data benefit differentially from these State-credits depending on which state their R&D is located. Tax credits are for R&D performed within the state that can be offset against state-level corporation tax liabilities. State-level corporation tax liabilities are calculated on total firm profits allocated across states according to a weighted combination of the location of firm sales, employment and property. Hence, any firm with an R&D lab within the state is likely to be liable both for state corporation tax (due to its employees and property in the state) and eligible for an offsetting R&D tax credit. Hence, inventor location appears to provide a good proxy for eligibility for state-level R&D tax credits.[54]

We estimate the spatial distribution of a firm's inventors from the USPTO patents file. The state component of the tax-price is therefore

$$\rho_{it}^{S} = \sum_{s} \theta_{ist} \rho_{st}^{S} \tag{B.3}$$

where ρ_{st}^{S} is the state level tax price and θ_{ist} is firm i's 10-year moving average share of inventors located in state s.

The second component of the tax price is based solely on Federal rules (ρ_{it}^{F}) and is constructed following Hall (1992) and Bloom, Criscuolo, Hall and Van Reenen (2008). The "Research and Experimentation" tax credit was first introduced in 1981 and has been in continuous operation and subject to many rule changes. It has a firm-specific component for several reasons. First, the amount of tax credit that can be claimed is based on the difference between actual R&D and a firm-specific "base". From 1981 to 1989 the base was the maximum of a rolling average of the previous three years' R&D. From 1990 onwards (except 1995-1996 when the tax credit lapsed) the base was fixed to be the average of the firm's R&D to sales ratio between 1984 and 1988, multiplied by current sales (up to a maximum of 16%). Start-ups were treated differently, initially with a base of 3%, but modified each year. Second, if the credit exceeds the taxable profits of the firm it cannot be fully claimed and must be carried forward. With discounting this leads to a lower implicit value of the credit for tax exhausted firms. Third, these firm-specific components all interact with changes in the aggregate tax credit rate (25% in 1981, 20% in 1990, 0% in 1995, etc.), deduction rules and corporate tax rate (which enters the denominator of equation (B.2)).

We implement the IV approach by first projecting the endogenous variable (R&D) on the instruments in the first stage. Table A2 shows the results from this estimation and demonstrates that the instruments have considerable power. Column (1) has the basic results, column (2) adds time dummies and column (3) also adds firm dummies. Even in the most general regression of the final column of Table A2 that is used in the later stages, the F-statistics are over 16. From this we calculate the value of R&D predicted by these tax credits, R_{it}^{TAX}, and then generate the stock of this using the standard perpetual inventory method, G_{it}^{TAX}. For each firm we then weight up other firms tax-credit predicted R&D stocks using SIC and $TECH$ to create the distance weighted instruments $TECHTAX$ and $SICTAX$. For example, for $TECHTAX_{it} = \sum_{j \neq i} TECH_{ij} G_{jt}^{TAX}$. We then use $\ln(TECHTAX)$ and $\ln(SICTAX)$ as instrumental variables for $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$ in the final stage regressions as presented in the last columns of Tables 3, 5 and 6. For the citation-weighted patent regressions we use a Negative Binomial equation, so to allow for endogeneity

[54] State level R&D tax credits can be generous, and vary differentially over states and time. For example, the five-largest R&D doing states had the following tax credit histories: California introduced an 8% credit in 1987, raised to 11%, 12% and 15% in 1997, 1999 and 2000 respectively. Massachussetts, New Jersey and Texas introduced 10%, 10% and 4% rates in 1991, 1994 and 2000 respectively. While Michigan has never introduced an R&D tax credit.

we take a control function approach (e.g. Aghion et al, 2005). We estimate the first stages for $\ln(SPILLTECH)$ and $\ln(SPILLSIC)$ and then include a fifth order series expansions of each of the residuals from these first stages in the final column of Table 4. We correct the standard errors using 1,000 bootstrap replications over firms.

We also considered an alternative approach of using $TECH$ and SIC weighted ρ_{it}^S and ρ_{it}^F as instrumental variables. However, the unbalanced nature of the panel makes this very unattractive as the value of the instruments changes as new firms exit and enter the sample. This generates a positive bias between R&D the user cost of R&D. For example, imagine a firm j enters a market. Then for some firm i for which $TECH_{ij} > 0$ there will be a rise in $SPILLTECH_{it}$ since there is now another firm doing R&D in its technology space. But its $TECH_{ij}$ weighted R&D user cost measure will also rise since the values of ρ_{jt}^S and ρ_{jt}^F for firm j are zero per entry (since they are missing) but strictly positive post entry.

B.3.2. Exogeneity of R&D tax credit policy changes

A concern is that changes to the R&D tax credit may be endogenous. Could states respond to falls in R&D by increasing the tax credit rate, for example. One check was to conduct experiments lagging the tax-credit instruments one and two periods, which led to qualitatively similar results. But we also investigated this issue further by reviewed the literature on US state R&D and corporate tax rates. Three facts are clear from this literature:

(1) State level tax credits have been gradually introduced across states over time. The first state R&D tax credit was introduced in Minnesota in 1982 following the introduction of the Federal Tax Credit in 1981, with 31 states having introduced credits by the end of 2005 (Wilson, 2005), and 38 states by 2010. The generosity of these credits has also been gradually trending up over time, rising from 6.25% in 1982 to 7.9% in 2005.

(2) The cross-sectional variation in credit rates is extremely large relative to the mean and growth rates of the average rate. The cross-sectional standard-deviation of credit rates is more than twice their mean. For example, the credit-rates range from 2.5% in South Carolina and Minnesota to 20% in Arizona and Hawaii. These rates also change frequently over time within states. For example, California changed its rate five times between its introduction in 1987 and 2010.

(3) The level and timing of introduction of the credits – which provides the empirical identification in our estimation given our firm and time dummies – seems to be uncorrelated with any observables after controlling for state and year fixed-effects. Papers which have tried to explain the evolution of state-level corporate tax credits have found that aggregate variables (such as the Federal credit rate) have some explanatory power, but local economic or political variables do not seem important (e.g. Chirinko and Wilson, 2008a,b). This partly reflects the long time delays in passing tax credits through state legislature, and also the fact the costs of many of these tax credits are small so that their adoption tends not to be strongly driven by budgetary concerns.

To investigate this issue further, we regressed the rate of the state R&D tax credit on lagged state R&D expenditures, a full set of state and year dummies, and the lagged value of the state tax credit (to control for dynamics). Using a variety of specifications with and without these controls, we could not find any predictive power for lagged state-level R&D expenditure or GDP per capita (a crude proxy for productivity) on current R&D tax credits. That is, prior state-level R&D expenditure does not seem to predict current levels of state R&D tax credits.

In summary, while state-level R&D tax credits have been rising since the early 1980s, this has happened at differential rates and levels across states, with this state-by-year differences in generosity seemingly uncorrelated with lagged economic or political variables. This suggests that the current level of R&D tax credits provides pseudo-random variation to identify corporate R&D expenditure in a regression including firm and year fixed effects.

B.4. Sample Selection Issues

To be in the final regression sample a firm has to have at least one patent granted (since 1963) in order to construct our measure of technological closeness (which requires patent information), so this does screen out firms who never patent. However, we do not require that a firm has several lines of business, only that it has some data in the Compustat Segment File (CSF) which contains the breakdown of sales across four-digit industry classes. Note that some firms operate solely in one class and are recorded as such (and we use their information). Nearly all firms in Compustat which have a patent are also in the CSF so this is not a source of sample selection.

The main source of selection is that we use the Compustat database that covers only publicly listed firms. This is because capital investment, R&D and other important variables are not required reporting items for privately listed firms. R&D is heavily concentrated on listed firms, however, so our sample accounts for a large proportion of the entire R&D in the US. For example, in 1995 the sum of R&D expenditures in our sample was \$79bn while the total industry R&D in the US was estimated as \$130bn by the NSF, so we cover about 62% of the total.

Of course it would be ideal to know the exact R&D of every firm, but this is not necessary for implementation of our technique. As we show in Appendix A.1 our comparative static results hold for any triple of firms. All we need is the thought experiment of increasing $SPILLTECH$ whilst holding $SPILLSIC$ constant (and vice versa).

There could be biases if, for a given firm we omit a relevant spillover. Certainly, the absence of other R&D performing firms will mean that we underestimate the R&D relevant spillovers for some firms. In general, it is unclear whether this would bias our estimates systematically in any one direction. If this generated classical measurement error, with random under-counting of spillovers, it would cause an attenuation bias towards zero. Thus, as you argue, there is the possibility that we underestimate the strength of both positive technology and negative product market spillovers. If this is so, our conclusion that both types of spillovers operate, one positive and the other negative, is strengthened.

Non-random exit relating to unobservables is very difficult to control for with existing techniques. Evidence from non-parametric control function techniques to control for selection in production functions suggests that the main form of bias comes from conditioning on a balanced panel (e.g. Olley and Pakes, 1996). Since our panel is unbalanced – we keep all entrants and exiters – this mitigates this problem. Non-random exit in the time series is also partially controlled for by the fixed effects.

B.5. The Bureau Van Dijk (BVD) Database

As noted in sub-section 6.3.2 the finance literature has debated the extent to which the breakdown of firm sales into four digit industries from the Compustat Segment Dataset is reliable. To address this concern, we used an alternative data source, the BVD (Bureau Van Dijk) database.

B.5.1. Description

The BVD data for the US is obtained from Dun and Bradstreet (D&B), which collects the data to provide credit ratings and to sell as a marketing database. These credit ratings are used to open bank accounts, and are also required for corporate clients by most large companies (e.g. Wal-Mart and General Electric) and the Government, so almost all multi-person establishments in the US are in the D&B database. Since this data is commercially used and sold for various financial and marketing purposes it is regularly quality checked by D&B. In Europe the BVD data comes from the National Registries of companies (such as Companies House in the UK), which have statutory requirements on reporting for all public and private firms. We used the primary and secondary four digit industry classes for every subsidiary within a Compustat firm that could be matched to BVD to calculate distribution of employment across four digit industries (essentially summing across all the global subsidiaries) as a proxy for sales by four digit industries.

The US data reports one primary four digit industry code and an ordered set of up to six secondary four digit industry codes. We allocated employment across sectors for an individual firm by assuming 75% of activity was in the primary industry code, 75% of the remainder in the main secondary code, 75% of this remainder in the next secondary industry code and so on, with the final secondary industry code containing 100% of the ultimate residual. In the European data firms report one primary industry code and as many secondary industry codes as they wish (with some firms reporting over 30) but without any ordering. Employment was allocated assuming that 75% of employees were in the primary industry code and the remaining 25% was split equally among the secondary industry codes. Finally, employment was added across all industry codes in every enterprise in Europe and the US owned by the ultimate Compustat parent to compute a four digit industry activity breakdown.

B.5.2. Matching to Compustat

We successfully matched three quarters of the Compustat firms in the original sample. The matched firms were larger and more R&D intensive than the non-matched firms. Consequently, these matched firms accounted for 84% of all employment and 95% of all R&D in the Compustat sample, so that judged by R&D the coverage of the BVD data of the Compustat sample was very good. The correlation between the Compustat Segment and BVD Dataset measures is reasonably high. The correlation between the sales share of firm i in industry k between the two datasets is 0.503. The correlation of $\ln(SPILLSIC)$ across the two measures is 0.592. The within-firm over-time variation of $\ln(SPILLSIC)$, which identifies our empirical results given that we control for fixed effects, reassuringly rises to 0.737. In terms of average levels both measures are similar, with an average SIC of 0.0138 using the Compustat measure and 0.0132 using the BVD measure. The maximum number of four digit industries for one of our firms, General Electric, is 213.

As an example of the extent of similarity between the two measures the Compustat and BVD SIC correlations for the four firms examines in the Case Study discussed in appendix D below are presented in Table A1. As can be seen the two measures are similar, IBM and Apple (PC manufacturers) are highly correlated on both measures and Motorola and Intel (semi-conductor manufacturers) are also highly correlated. But the correlation across these two pairs is low. There are also some differences, for example the BVD-based measure of SIC finds that IBM is closer in sales space with Intel and Motorola (SIC = 0.07) then the Compustat-based measure (SIC = 0.01). This is because IBM uses many of its own semi-conductor chips in its own products so this is not included in the sales figures. The BVD based measure picks these up because IBM's three chip making subsidiaries are tracked in the ICARUS data even if their products are wholly used within IBM's vertically integrated chain.

B.5.3. Coverage

The industry coverage was broader in the BVD data than the Compustat Segment Dataset. The mean number of distinct four digit industry codes per firm was 13.8 in the BVD data (on average there were 29.6 enterprises, 18.2 in Europe and 11.4 in the US) compared to 4.6 in the Compustat Segment files. This confirms Villalonga's (2004) finding that the Compustat Segment Dataset underestimates the number of industries that a firm operates in.

C. Alternative Distance Metrics

C.1. Robustness to Aggregation

The standard Jaffe measure, $TECH^J$, differs from the Jaffe covariance (and Exposure) measure, $TECH^{J-COV}$ because it is an (uncentered) correlation, rather than covariance, between the vectors F_i and $F_j : TECH^J_{ij} = \frac{F_i F_j'}{(F_i F_i')^{1/2}(F_j F_j')^{1/2}}$. We now show that this normalization has the advantage that it makes the index less sensitive to the aggregation of technology fields. We refer to this property as 'robustness to aggregation'.

To see this formally, consider the case where technology fields $\Upsilon - 1$ and Υ are aggregated, and define the $1x(\Upsilon - 1)$ vector $F_i^* = (F_{i1}, ..., F_{i,\Upsilon-2}, F_{i\Upsilon-1} + F_{i,\Upsilon-2})$. The new $TECH^{J-COV}$ index can be expressed as

$$F_i^* F_j^{*\prime} = F_i F_j' + (F_{i,\Upsilon-1} F_{j\Upsilon} + F_{j,\Upsilon-1} F_{i\Upsilon}) \geq F_i F_j'$$

and strict inequality holds if each firm operates in at least one of the two aggregated fields, $\Upsilon - 1$ and Υ. This shows that $TECH^{J-COV}$ increases as a consequence of aggregation. This is an unattractive property. The standard $TECH^J$ measure mitigates this aggregation bias because it normalizes by the standard deviations of the vectors F_i^* and F_j^*,which also increase (since $F_i^* F_i^{*\prime} = F_i F_i' + 2F_{i,\Upsilon-1} F_{i\Upsilon} \geq F_i F_i'$).

Define $\phi_{ij} = \frac{F_{i,\Upsilon-1} F_{j\Upsilon} + F_{j,\Upsilon-1} F_{i\Upsilon}}{F_i F_j'}$, $\phi_{ii} = \frac{2F_{i,\Upsilon-1} F_{i\Upsilon}}{F_i F_i'}$ and $\phi_{jj} = \frac{2F_{j,\Upsilon-1} F_{j\Upsilon}}{F_j F_j'}$. Letting asterisks denote the index based on the aggregated technology fields, it follows immediately that

$$\begin{aligned} TECH^{J^*} &= \lambda TECH^J \\ TECH^{J-COV^*} &= \theta TECH^{J-COV} \end{aligned}$$

where $\lambda = \frac{1+\phi_{ij}}{\{(1+\phi_{ii})(1+\phi_{jj})\}^{1/2}} < \theta = 1 + \phi_{ij}$. That is, aggregation leads to a smaller percentage increase in $TECH^J$ than in the $TECH^{J-COV}$ index. This is sense in which the Jaffe index is less sensitive to aggregation than the Jaffe covariance measure.[55]

Note that it is straightforward to generalize the results in this sub-section to the case where more than two technology fields are aggregated, and to the case where several subsets of fields are aggregated. An example of the latter is moving from, say, four-digit to three-digit classification of fields.

[55] In general we cannot know whether $\lambda \lesseqgtr 1$. This depends on the specific distributions of firm R&D across technology fields. It is possible that aggregation reduces the $TECH^J$ index. But we can say that, if aggregation increases that measure, the increase will be proportionately smaller than for the $TECH^{J-COV}$ index.

C.2. Mahalanobis

To explain the calculation of the Mahalanobis normed measure we need to define some notation. First, we let $T = [T_1', T_2'...T_N']$ denote the $(426, N)$ matrix where each row contains a firm's patent shares in the 426 technological classes. Second, we define a normalized $(N, 426)$ matrix $\tilde{T} = [T_1'/(T_1T_1')^{1/2}, T_2'/(T_2T_2')^{1/2}...T_N'/(T_NT_N')^{1/2}]$, in which each row is simply normalized by the firm's patent share dot product. Third, we define the (N, N) matrix $TECH = \tilde{T}'\tilde{T}$. This matrix $TECH$ is just the standard Jaffe (1986) uncentered correlation measure between firms i and j, in which each element is the measure $TECH_{ij}$, exactly as defined in (3.6) above. Fourth, we define a $(426, N)$ matrix $\widetilde{X} = [T_{(:,1)}'/(T_{(:,1)}'T_{(:,1)})^{1/2}...T_{(:,N)}'/(T_{(:,N)}'T_{(:,N)})^{1/2}]$ where $T_{(:,i)}$ is the i^{th} column of T. This matrix $\widetilde{X}$ is similar to $\widetilde{T}$, except it is the normalized patent class shares across firms rather than firm shares across patent classes. Finally, we can define the $(426, 426)$ matrix $\Omega = \widetilde{X}\widetilde{X}\,'$in which each element is the standard Jaffe (1986) uncentered correlation measure between patent classes (rather than between firms). So, for example, if patent classes i and j coincide frequently within the same firm, then Ω_{ij} will be close to 1 (with $\Omega_{ii} = 1$), while if they never coincide within the same firm Ω_{ij} will be 0.

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

D. Case Studies of Particular Firms

There are numerous case studies in the business literature of how firms can be differently placed in technology space and product market space. Consider first firms that are close in technology but sometimes far from each other in product market space (the bottom right hand quadrant of Figure 1). Table A1 shows IBM, Apple, Motorola and Intel: four high highly innovative firms in our sample. We show results for $SPILLSIC$ measured both by the Compustat Segment Database and the BVD Database. These firms are close to each other in technology space as revealed by their patenting. IBM, for example, has a $TECH$ correlation of 0.76 with Intel, 0.64 with Apple and 0.46 with Motorola (the overall average $TECH$ correlation in the whole sample is 0.038 - see Table 9). The technologies that IBM uses for computer hardware are closely related to those used by all these other companies. If we examine SIC, the product market closeness variable, however, there are major differences. IBM and Apple are product market rivals with a SIC of 0.65 (the overall average SIC correlation in the whole sample is 0.015 - see Table 9). They both produced PC desktops and are competing head to head. Both have presences in other product markets of course (in particular IBM's consultancy arm is a major segment of its business) so the product market correlation is not perfect. By contrast IBM (and Apple) have a very low SIC correlation with Intel and Motorola (0.01) because the latter firms mainly produce semi-conductor chips not computer hardware. IBM produces relatively few semi-conductor chips so is not strongly competing with Intel and Motorola for customers. The SIC correlation between Intel and Motorola is, as expected, rather high (0.34) because they are both competitors in supplying chips. The picture is very similar when we look at the measures of SIC based on BVD instead of Compustat, although there are some small differences. For example, IBM appears closer to Intel (BVD $SIC = 0.07$) because IBM produces semi-conductor chips for in-house use. This is largely missed in the Compustat Segment data, but will be picked up by the BVD data (through IBM's chip-making affiliates).

At the other end of the diagonal (top left hand corner of Figure 1) there are many firms who are in the same product market but using quite different technologies. One example from our dataset is Gillette and Valance Technologies who compete in batteries giving them a product market closeness measure of 0.33. Gillette owns Duracell but does no R&D in this area (its R&D is focused mainly personal care products such as the Mach 3 razor and Braun electronic products). Valence Technologies uses a new phosphate technology that is radically improving the performance of standard Lithium ion battery technologies. As a consequence the two companies have little overlap in technology space ($TECH\ = 0.01$).

A third example is the high end of the hard disk market, which are sold to computer manufacturers. Most firms base their technology on magnetic technologies, such as the market leader, Segway. Other firms (such as Phillips) offer hard disks based on newer, holographic technology. These firms draw their technologies from very different areas, yet compete in the same product market. R&D done by Phillips is likely to pose a competitive threat to Segway, but it is unlikely to generate useful knowledge spillovers for Segway.

E. Endogenous Choice of Technology Classes

E.1. The Basic Approach

One way to provide a micro-foundation for a distance metric for technological closeness is to draw explicitly on the economic geography literature. Simple economic geography models can show how firms may optimally choose the geographic location of their plants to benefit from potential spillovers and natural advantages leading to agglomeration and coagglomeration patterns. We draw heavily on this work (in particular, Ellison and Glaeser, 1997; Ellison, Glaeser and Kerr, 2007, 2010) to consider a more micro-founded model of our empirical measures of $TECH_{ij}$. However, rather than choosing which geographical classes to locate in, we will consider a firm's choice of which *technological* areas to locate in and consider co-location patterns in this dimension.

E.2. Agglomeration and coagglomeration measures

Consider extending the model in Section 2 to allow for a period 0 where each firm i chooses to direct its R&D across particular technological classes, $\tau = 1, ..., \Upsilon$. A firm can choose to invest in one or more technological classes by establishing some R&D labs (denoted lab l) in these different classes. Assume that there are a fixed number of R&D employees in each lab, e_l. When choosing a technological profile a firm will consider a number of factors including the underlying technological opportunities in the class (common to all firms[56]), R&D lab l's ability in a particular field as well as the other labs who have already located in this area as there are potentially spillovers.

[56] Thus the number of potential inventions is higher in some areas like bio-pharmaceuticals than others (like cement).

We will model this explicitly below in a firm location model, but we first define some key indexes. A raw technological concentration measure for firm i is

$$G_i = \sum_{\tau=1}^{\Upsilon} (T_{i\tau} - x_\tau)^2$$

where $T_{i\tau}$ is the proportion of all firm i's R&D employment (or equivalently, the proportion of R&D labs) in technology area τ and x_τ is the share of total R&D employment in the economy in technology area τ.Ellison and Glaeser (1997) suggest an agglomeration measure of the form:

$$\gamma_i \equiv \frac{G_i/(1-\sum_\tau {x_\tau}^2) - H_i}{1-H_i} \tag{E.1}$$

where H_i is a "Herfindahl Index" reflecting how concentrated are a firm's R&D labs[57].

Ellison and Glaeser (1997) also suggest a coagglomeration measure. In our context consider a group of I firms and w_i is firm i's share of the group's total R&D employment. Let $T_1, ..., T_\Upsilon$ be the share of R&D employment in the group of I firms in each technology area. G is the raw geographic concentration for the I firm group ($G = \sum_\tau (T_\tau - x_\tau)^2$) and H is the Herfindahl Index of the I-firm group ($H = \sum_i w_i^2 H_i$). The coagglomeration measure is:

$$\gamma^C \equiv \frac{G/\left(1-\sum_\tau {x_\tau}^2\right) - H - \sum_{i=1}^{I} \gamma_i w_i^2 (1-H_i)}{1-\sum_{i=1}^{I} w_i^2} \tag{E.2}$$

The particular form of this is motivated by relating the index to an explicit location choice model.

Proposition E.1. *In an I firm probabilistic location choice model, suppose that the indicator variables $\{u_{l\tau}\}$ for whether the l-th lab locates in technological area τ satisfies $E(u_{l\tau}) = x_\tau$ and* $Corr(u_{l\tau}, u_{l'\tau}) = \begin{matrix} \gamma_i \text{ if labs } l \text{ and } l' \text{ both belong to firm } i \\ \gamma_0 \text{ if labs } l \text{ and } l' \text{ belong to different firms} \end{matrix}$

then $E(\gamma^C) = \gamma_0$

The value of Proposition 1 is that under the given assumptions the coagglomeration index in equation (E.2) based on empirically observable measures recovers an estimate of the unobserved "deep parameter", γ_0, which is relevant to the spillover effect.

[57] $H_i = \sum_\tau (1/e_{l\tau})^2$ where $e_{i\tau}$ is the employment in lab l in technology class τ for firm i. Since we have assumed that all labs are equally sized $H_i = \sum_\tau (1/L_i)^2$ where L_i is the number of R&D labs owned by firm i. Obviously if a firm has only one R&D lab it will have a high degree of measured agglomeration as it can only locate in one class, but this is a rather artifical type of specialization and the presence of H_i in equation (E.1) corrects for this.

E.3. A model of the choice of technological class

To simplify notation we focus on the case of two firms so $I = 2$. In this case the coagglomeration measure γ^C will be [58]:

$$\gamma^C \equiv \frac{\sum_\tau (T_{1\tau} - x_\tau)(T_{2\tau} - x_\tau)}{1 - \sum_\tau x_\tau^2} \tag{E.3}$$

where L_1 is the number of labs belonging to firm 1 and L_2 the in firm 2. Labs are indexed by $l \in L_1 \cup L_2$ with L_1 being the labs in firm 1 and L_2 the labs in firm 2. Firms choose where to locate labs between Υ technology classes. Spillovers imply that lab l's profits are a function of the other labs' location decisions. If there is a potentially positive spillover between lab l and l' they will tend to be located in the same technology class.

We follow Ellison and Glaeser (1997, 2007) in considering "all or nothing" spillovers as this reduces substantially the problem of multiple equilibria in the lab location game. In particular, define a partition ω of $L_1 \cup L_2$ to be a correspondence $\omega : L_1 \cup L_2 \rightrightarrows L_1 \cup L_2$ such that $l \in \omega(l)$ for all l and $l' \in \omega(l) \implies \omega(l) = \omega(l')$. Suppose lab location decisions are the outcome of a game in which the labs choose technology classes in some exogenously specified order and lab l's profits from locating in technology area τ are given by:

$$\ln(\pi_{l\tau}) = \ln(x_\tau) + \sum_{l' \in \omega(l)} I(l_{l'} \neq \tau)(-\infty) + \epsilon_{l\tau} \tag{E.4}$$

The first term on the right hand side of equation (E.4), x_τ, is the "fecundity" of the technology area, τ. The middle term reflects spillovers: a spillover exists between labs l and l' if $l' = \omega(l)$ and that when spillovers exist they are sufficiently strong to outweigh all other factors in a firm's decision about whether to locate a lab in this technology class. The third term is $\epsilon_{l\tau}$ a Weibull distributed random shock that is independent across labs and locations.

Under these conditions it is possible to prove:

Proposition E.2. *Consider the model of technological area choice described above:*
(a) The Perfect Bayesian Equilibrium (PBE) is unique. In equilibrium each lab l chooses technology class τ that maximizes $\ln(x_\tau) + \epsilon_{l\tau}$ if no lab with $l' \in \omega(l)$ has previously chosen a technology class, and chooses the same technology class of previously located labs if some such labs have chosen this location.
(b) If $0 \leq \gamma_0^S \leq \gamma_1^S, \gamma_2^S$ or $0 \leq \gamma_0^S \leq \gamma_1^S \gamma_2^S$ and $0 \leq \gamma_0 \leq \min(1/L_1, 1/L_2)$, then there exist distributions over the set of possible partitions for which:

$$Prob(l' \in \omega(l)) = \begin{array}{c} \gamma_i^S \textit{ if labs } l \textit{ and } l' \textit{ both belong to firm } i \\ \gamma_0^S \textit{ if labs } l \textit{ and } l' \textit{ belong to different firms} \end{array}$$

(c) If the distribution satisfies the condition in part (b), then in any PBE of the model the agglomeration and coagglomeration indexes satisfy $E(\gamma^C) = \gamma_0^S$ and $E(\gamma_i) = \gamma_i^S$.

Proof. See Ellison et al (2007), Appendix A. ■

The proposition shows the conditions under which calculation of the coagglomeration index γ^C is an unbiased estimate of the deep parameter γ_0^S . Thus, it gives some theoretical foundation of a distance metric that we use in our empirical work. Proposition E2 shows that the framework developed has a degree of robustness to equilibrium selection.

[58] Note that this will be specific to any given pair of firms (i.e. γ_{12}^C) but we drop the subscripts for simplicity.

In our context, equation (E.3) becomes

$$\gamma_{ij}^C \equiv \frac{\sum_\tau (T_{i\tau} - x_\tau)(T_{j\tau} - x_\tau)}{1 - \sum_\tau x_\tau^2}$$

which is the alternative distance metric used in sub-section 6.1.

E.4. Extensions

The model is obviously specialized, but can be extended in various dimensions. First, the model can be extended to allow for other reasons for coagglomeration patterns such as "natural advantage". It is difficult to separately identify these from spillovers and in general the indexes will capture elements of both. In the context of our paper, we seek to separate spillovers from common clusters of technological opportunity by explicitly examining how shocks to a firm's R&D differentially effect other firms who are "close neighbors" (as indicated by γ^C) relative to those who are more distant. If there are genuine spillovers, the close neighbors will be more affected (e.g. in the productivity) than those who are distant. This would not be the case were natural advantage (clusters of common technological opportunity) were fixed. If these changed over time, then the identification problem would reappear. This is why we use tax-policy changes to R&D as instrumental variables as we argue that these are orthogonal to such common technology shocks.

A second limitation is that the framework does not allow for product market rivalry. Section 2 shows how this can be allowed for in later stages of the game. It is harder to consider a framework for product choice. The Ellison-Glaeser framework is not well adapted for this as firms will suffer a negative spillover and will want to locate away from where firms currently are in general, rather than be close as in equation (E.4).

Finally, note that equation (E.4) is quite restrictive. Not only do the errors take an independent parametric form, we assume all classes are neither complements nor substitutes so each lab can be seen as making an profit maximizing decision independent of the identity of the firm who owns the lab. We show how this can be relaxed in our Mahalanobis measure which allows differential degrees of closeness between technology classes. If these were literally geographic distances, we could use the actual distance in travel times or miles, as in Duranton and Overman (2005).

F. 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. An interesting extension of the methodology outlined here is to examine particular industries in much greater detail. This is difficult to do, given the size of our dataset. Nevertheless, it would be worrying if the basic theory was contradicted in the high-tech sectors, as this would suggest our results might be due to biases induced by pooling across heterogenous sectors. To investigate this, 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. *Computer hardware* covers SIC 3570 to 3577 (Computer and Office Equipment (3570), Electronic Computers (3571), Computer Storage Devices (3572), Computer Terminals (3575), Computer Communications Equipment (3576)and Computer Peripheral Equipment Not Elsewhere classified (3577). *Pharmaceuticals* includes Pharmaceutical Preparations (2834) and In Vitro and In Vivo Diagnostic Substances

(2835). *Telecommunications Equipment* covers Telephone and Telegraph Apparatus (3661), Radio and TV Broadcasting and Communications Equipment (3663) and Communications Equipment not elsewhere classified (3669).

Table A4 summarizes the results from these experiments. The results for computer hardware (Panel A) are qualitatively similar to the pooled results. Despite being estimated on a much smaller sample, $SPILLTECH$ has a positive and significant association with market value and $SPILLSIC$ a negative and significant association. There is also evidence of technology spillovers in the production function and the patenting equation. $SPILLSIC$ is positive in the R&D equation indicating strategic complementarity and is not significant in patents or productivity regressions, as our model predicts.

The pattern in pharmaceuticals is very similar, with the parameters being consistent with the predicted signs from the theory and statistically significant. Technology spillovers are also found in the production function and the patents equation and there is also evidence of strategic complementarity, as indicated by the large coefficient on $SPILLSIC$ in the R&D equation. We find a much larger, negative coefficient on $SPILLSIC$ in the market value equation than in the pooled results, indicating substantial business stealing effects in this sector. We will return to this finding in the next sub-section when we discuss the private and social returns to R&D.

The results are slightly different in the telecommunications equipment industry. We also observe significant technology spillover effects in the market value equation and citation-weighted patents equations, but the coefficient on $SPILLTECH$ is insignificant (although positive) in the productivity equation. There is no evidence of significant business stealing or strategic complementarity of R&D in this sector, however.

Like the pooled sample, these findings on technological spillovers and business stealing are robust to treating R&D as endogenous. For example, in the IV estimation the coefficients (*standard error*) on $SPILLTECH$ and $SPILLSIC$ in the market value equation for computer hardware are 2.314 (*0.668*) and -0.512 (*0.243*) respectively.[59]

Overall, the qualitative results from these high-tech sectors indicate that our main results are broadly present in those R&D intensive industries where we would expect our theory to have most bite. Technology spillovers are found in all three sectors, with larger coefficients than in the pooled results, as we would expect.[60] However, there is also substantial heterogeneity across the sectors. First, the size 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 two of the three industries studied. Finally, there is evidence of strategic complementarity in R&D for computers and drugs, but not for telecommunications.

[59] These same coefficients (*standard errors*) on $SPILLTEC$ and $SPILLSIC$ in the market value equation for pharmaceuticals and telecommunications equipment are 3.139 (*1.456*) and -1.317 (*1.427*), and 2.500 (*0.696*) and -0.113 (*0.540*) respectively.

[60] We also examined industry heterogeneity in terms of technology levels, defined as the average ratio of R&D/Sales ratio in the four digit industry. We interacted this with $SPILLTECH$ and $SPILLSIC$ in each of the Tobin's Q, patents, productivity and R&D equations. The coefficients on spillovers tended to be larger in absolute magnitude, but only one of these eight interactions was significant at the 5% level ($SPILLTECH$ in the productivity equation which had a coefficient (*standard error*) of 1.035 (*0.497*)). This is mild evidence for the greater importance of spillovers in high tech industries as in Table A4.

G. Computing Private and Social Returns to R&D

G.1. Roadmap

In this Appendix we show how to compute the private and social returns to R&D in the analytical framework developed in this paper. Sub-section G.2 provides some basic notation, following the presentation in the empirical section of the paper, and derives some "reduced forms" after substituting out all the interactions operating through the spillover terms. The main results are in sub-section G.3. which calculates the general form of the marginal social and private returns to R&D to an arbitrary firm.

We define the marginal social return (MSR) to R&D for firm i as the increase in aggregate output generated by a unit increase in firm i's R&D stock (taking into account the induced changes in R&D by other firms). The marginal private return (MPR) is defined as the increase in firm i's output generated by a marginal increase in its R&D stock. 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. For the computations presented in the text we use the general formulae developed here, but we also show below that the key intuition can be understood by examining the special case where all firms are symmetric and there is no "amplification" effect (due to the presence of product market spillovers in the R&D equation). In this case, the wedge between the social and private returns can be either positive or negative, as it depends upon the importance of technology spillovers in the production function (φ_2) relative to product market rivalry effects in the market value equation (γ_3). Social returns will be larger when φ_2 is larger and private returns will be larger as (the absolute value of) γ_3 rises. Both private and social returns increase in the effect of R&D on output (φ_1).

G.2. Basic Equations

The empirical specification of the model consists of four equations: R&D, Tobin's Q, productivity and patents. For purposes of evaluating rates of return to R&D, we do not need the patent equation because there is no feedback from patents to these other endogenous variables in our model. Thus for this analysis we use only the R&D, market value and productivity equations.

We examine the long run effects in the model, setting $R_{it} = R_i$ and $Y_{it} = Y_i$ for all t, and $G_j = \frac{R_j}{\delta}$, where R is the flow of R&D expenditures, Y is output, G is the R&D stock and δ is the depreciation rate used to construct G. The model can be written as

$$\ln R_i = \alpha_2 \ln \sum_{j\neq i} TECH_{ij} R_j + \alpha_3 \ln \sum_{j\neq i} SIC_{ij} R_j + \alpha_4 X_{1i} + \ln Y_i \tag{G.1}$$

$$\ln(V/A)_i = \gamma_1 \ln(R/A)_i + \gamma_2 \ln \sum_{j\neq i} TECH_{ij} R_j + \gamma_3 \ln \sum_{j\neq i} SIC_{ij} R_j + \gamma_4 X_{2i} \tag{G.2}$$

$$\ln Y_i = \varphi_1 \ln R_i + \varphi_2 \ln \sum_{j\neq i} TECH_{ij} R_j + \varphi_3 \ln \sum_{j\neq i} SIC_{ij} R_j + \varphi_4 X_{3i} \tag{G.3}$$

where V/A is Tobin's Q, X_1, X_2 and X_3 are vectors of control variables (for ease of exposition we treat them as scalars), and the depreciation rate δ gets absorbed by the constant terms in each of the equations (which we suppress for brevity). We then solve out the cross equation links with Y_i by substituting equation (G.3) into equations (G.1). This yields a new equation for R&D:

$$\ln R_i = \alpha_2' \ln \sum_{j \neq i} TECH_{ij} R_j + \alpha_3' \ln \sum_{j \neq i} SIC_{ij} R_j + \alpha_4' X_{1i} \tag{G.4}$$

where $\alpha_1' = \frac{\alpha_1+\varphi_1}{(1-\varphi_1)}, \alpha_2' = \frac{\alpha_2+\varphi_2}{(1-\varphi_1)}$, $\alpha_3' = \frac{\alpha_3+\varphi_3}{(1-\varphi_1)}$ and $\alpha_4' = \frac{\alpha_4+\varphi_4}{(1-\varphi_1)}$. The model we use for the calculations in this Appendix is given by equations (G.4), (G.2) and (G.3).

We take a first order expansion of $\ln [\sum_{j \neq i} TECH_{ij} R_j]$ and $\ln [\sum_{j \neq i} SIC_{ij} R_j]$, approximating them in terms of $\ln R$ around some point, say $\ln R^0$. Take first $f^i = \ln [\sum_{j \neq i} TECH_{ij} R_j] = \ln [\sum_{j \neq i} TECH_{ij} \exp(\ln R_j)]$. Approximating this nonlinear function of $\ln R$,

$$\begin{aligned} f^i &\simeq \{\ln \sum_{j \neq i} TECH_{ij} R_j^0 - \sum_{j \neq i} (\frac{TECH_{ij} R_j^0}{\sum_{j \neq i} TECH_{ij} R_j^0}) \ln R_j^0\} + \sum_{j \neq i} (\frac{TECH_{ij} R_j^0}{\sum_{j \neq i} TECH_{ij} R_j^0}) \ln R_j \\ &\equiv a_i + \sum_{j \neq i} b_{ij} \ln R_j \end{aligned}$$

where a_i reflects the terms in large curly brackets and b_{ij} captures the terms in parentheses in the last terms.

Now consider the term $g^i = \ln [\sum_{j \neq i} SIC_{ij} R_j]$.By similar steps

$$\begin{aligned} g^i &\simeq \{\ln \sum_{j \neq i} SIC_{ij} R_j^0 - \sum_{j \neq i} [\frac{SIC_{ij} R_j^0}{\sum_{j \neq i} SIC_{ij} R_j^0}] \ln R_j^0\} + \sum_{j \neq i} (\frac{SIC_{ij} R_j^0}{\sum_{j \neq i} SIC_{ij} R_j^0}) \ln R_j \\ &\equiv c_i + \sum_{j \neq i} d_{ij} \ln R_j \end{aligned}$$

Using these approximations, we can write the R&D equation (G.4)as

$$\ln R_i = \lambda_i + \sum_{j \neq i} \theta_{ij} \ln R_j + \alpha_4' X_{1i}$$

where $\lambda_i = \alpha_2' a_i + \alpha_3' c_i$ and $\theta_{ij} = \alpha_2' b_{ij} + \alpha_3' d_{ij}$. Let $\lambda, \ln R$ and X be $Nx1$ vectors, and define the NxN matrix $H = \begin{bmatrix} 0 & \theta_{ij} \\ \theta_{ij} & 0 \end{bmatrix}$. Then the R&D equation in matrix form is

$$\ln R = \Omega^{-1} \lambda + \alpha_4' \Omega^{-1} X_1 \tag{G.5}$$

where $\Omega = I - H$.

By a similar derivation, we can write the production function as

$$\ln Y_i = \psi_i + \varphi_1 \ln R_i + \sum_{j \neq i} \delta_{ij} \ln R_j + \varphi_4' X_{3i}$$

where $\psi_i = \varphi_2 a_i + \varphi_3 c_i$ and $\delta_{ij} = \varphi_2 b_{ij} + \varphi_3 d_{ij}$. Let ψ be an $Nx1$ vector and define the NxN matrix $M = \begin{bmatrix} \varphi_1 & \delta_{ij} \\ \delta_{ij} & \varphi_1 \end{bmatrix}$. Then the production function in matrix form is

$$\ln Y = \psi + M \ln R + \varphi_4' X_3 \tag{G.6}$$

Finally, the market value equation can be expressed as

$$\ln(V/A)_i = \phi_i - \gamma_1 \ln A_i + \gamma_1 \ln R_i + \sum_{j \neq i} \omega_{ij} \ln R_j + \gamma_4' X_{2i}$$

where $\phi_i = \gamma_2 a_i + \gamma_3 c_i$ and $\omega_{ij} = \gamma_2 b_{ij} + \gamma_3 d_{ij}$. Letting ϕ be an $Nx1$ vector and defining the NxN matrix $\Gamma = \begin{bmatrix} \gamma_1 & \omega_{ij} \\ \omega_{ij} & \gamma_1 \end{bmatrix}$, the value equation in matrix form is

$$\ln V/A = \phi - \gamma_1 \ln A + \Gamma \ln R + \gamma_4 X_2 \tag{G.7}$$

The model is summarized by equations (G.5), (G.6) and (G.7).

G.3. Deriving the Private and Social Return to R&D

G.3.1. General Case

To derive the private and social rates of return to R&D, we consider the effect of a one percent increase in the stock of R&D by firm i. Since in steady state the stock is proportional to the flow of R&D ($G = \frac{R}{\delta}$), we can capture this effect by setting $d \ln R_i = \alpha_4' dX_{1i} = 1$ and zero for $j \neq i$.[61] Using the R&D equation (G.5), the absolute changes in R&D levels, after amplification, are given by the $Nx1$ vector $dR = B_R \Omega^{-1} z^*$, where z^* is an $Nx1$ vector with one in the i^{th} position and zeroes elsewhere, and B_R is an NxN matrix with R_i in the i^{th} diagonal position and zeroes elsewhere. From the production function (G.6), this induces changes in productivity (output, given the levels of labor and capital) which are given by $dY = B_Y M \Omega^{-1} z^*$, where B_Y denotes an NxN matrix with Y_j in the j^{th} diagonal position ($j = 1, ..., N$) and zeroes elsewhere.

This computation of the output effects is correct for the steady state analysis. Recall that we define the marginal social return (MSR) to R&D for firm i as the increase in aggregate output associated with a unit increase in firm i's R&D stock (not a unit increase it its R&D flow), taking into account the induced changes in R&D by other firms. Therefore, we need to divide the aggregate output gain by the increase in the stock of R&D for firm i and any other firms whose R&D is induced by the change, which is given by $dG'z = \frac{1}{\delta} dR'z$,where z is an $Nx1$ vector of ones. Thus we can write the MSR as follows:

$$MSR_i = \frac{dY'z}{dG'z} \tag{G.8}$$

Note that the MSR is a scalar.

The marginal private return (MPR) is defined as the increase in firm i's output generated by a unit increase in its R&D stock (any induced R&D by other firm's is not relevant to this computation). The MPR consists of two parts. The first is the increase in firm $i's$ output, given its levels of labor and capital. This increase is given by $z^{*\prime} dY$,where z^* is an $Nx1$ vector with one in the i^{th} position and zeroes elsewhere. In addition, the firm enjoys output gains through the business stealing effect. This will be reflected in an increase in the level of labor and capital used by the firm (holding the level of *productivity constant*). Thus we cannot compute business stealing gains directly from the effect of R&D in the production function.

[61] We scale by 100 here – one percent is taken as 1. In the final calculations the change in R&D stock is divided by 100.

To compute these gains, we exploit the impact of business stealing in the market value equation. To isolate the impact of business stealing ($SPILLSIC$) on market value, we hold the productivity level constant by 'turning off' the effect of own R&D ($\gamma_1 = 0$) and $SPILLTECH$ ($\gamma_2 = 0$). Define the NxN matrix $\Gamma^* = \begin{bmatrix} 0 & \omega^*_{ij} \\ \omega^*_{ij} & 0 \end{bmatrix}$ where $\omega^*_{ij} = \gamma_3 d_{ij} \leq 0$ ($j \neq i$). From (G.7), the induced percentage change in market value is

$$d \ln V^* = \Gamma^* d \ln G = \Gamma^* \Omega^{-1} z^*$$

The change in market value associated with the business stealing effect, $d \ln V^*$, can be decomposed into two parts – a change in the level of output and shifts in the price-cost margin of the firm. In order to compute the private return to R&D in terms of output gains, we need to separate the estimated value effect of R&D into these the output and price effects. We assume that a fraction σ of the overall change in market value is due to changes in output (the case $\sigma = 1$ corresponds to the case where the price-cost margin is constant – in particular, not affected by $SPILLSIC$). We discuss later how we choose the empirical value of σ for the computations. Using this value, we can write the absolute output changes associated with business stealing as $dY^* = \sigma B_Y \Gamma^* \Omega^{-1} z^*$.[62]

There is a change in output due to business stealing for each firm. The change for firm j is distributed to (or from) all other firms in general, and we need to describe what that depends on. Consistent with the original formulation of $SPILLSIC$, we assume the fraction of the overall loss by firm j which goes to firm i, which we call s_{ji}, depends the closeness of the two firms, SIC_{ji}, and on how much firm i changes its R&D, which is what induces the redistribution, dR_i. Following our earlier derivation of the linear approximation to the system, we use

$$s_{ji} = \frac{SIC_{ji} dR_i}{\sum_{k \neq j} SIC_{jk} dR_k}$$

As required, these weights add up to one over all recipient firms.

Let z^{**}denote an $Nx1$ vector with $+1$ in the i^{th} position and $-s_{ji}$ in the $j \neq i$ positions. Then we can write the total change in firm i's output as $dY'z^* + dY^{*\prime}z^{**}$. The first is the direct gain in output by firm i, and the second component is the redistribution of output from other firms to firm i. The marginal private return to R&D is the total output gain by firm i divided by the increase in the R&D stock by firm i :

$$MPR_i = \frac{dY'z^* + dY^{*\prime}z^{**}}{dG'z^*} \tag{G.9}$$

A comparison of the expressions for MSR and MPR, in equations (G.8) and (G.9), shows that we cannot say which is larger a priori. The MSR and MPR differ in three respects: 1) the MSR is larger because it includes productivity (output) gains from firms other than i due to technology spillovers in the numerator, 2) the MSR is smaller than the MPR because it also counts the full R&D costs of other firms (if there is amplification) in the denominator, and 3) the MSR is also smaller because the MPR counts output gains for the firm through the business stealing effects, while the social return excludes them.

[62] Note that if there is no amplification effect in R&D ($\Omega = I$), then all firms lose output to firm i. But when there is amplification, this need not be true, and in fact even firm i can end up losing output to other firms whose R&D was increased by amplification. It all depends on the pattern of amplification and firms' positions in product space (i.e., on Ω and Γ^*).

G.3.2. Special Case: No R&D Amplification

Consider the case where there is no R&D amplification effect ($\Omega = I$) and no $SPILLSIC$ effect on output ($\varphi_3 = 0$). In this case the earlier formula for dY reduces to:

$$dY = \begin{pmatrix} \varphi_1 Y_1 & \delta_{12} Y_1 & \delta_{1N} Y_1 \\ \delta_{21} Y_2 & \varphi_1 Y_2 & \delta_{12} Y_1 \\ \delta_{N1} Y_N & \delta N_{N2} Y_N & \varphi_1 Y_N \end{pmatrix} z^* = \begin{pmatrix} \delta_{1i} Y_1 \\ \delta_{2i} Y_2 \\ \varphi_1 Y_i \\ \delta_{Ni} Y_N \end{pmatrix}$$

where again z^* is an $Nx1$ vector with one in the i^{th} position and zeroes elsewhere. It follows that $dY'z = \varphi_1 Y_i + \sum_{j \neq i} \delta_{ji} Y_j$, so the marginal social return for firm i can be expressed as

$$MSR_i = \boldsymbol{\varphi}_1 \frac{Y_i}{G_i} + \boldsymbol{\varphi}_2 \frac{\sum_{j \neq i} b_{ji} Y_j}{G_i}$$

The MSR depends on the coefficients of own R&D and technology spillovers in the production function, and the technology spillover linkages across firms. The term $\varphi_2 \frac{\sum_{j \neq i} b_{ji} Y_j}{G_i}$ captures the marginal impact of an increase in firm i's R&D stock on all other firms' output levels, which are mediated by the technology linkages between firm i and other firms.

In the fully symmetric case where all firms are identical both in size *and* technology spillover linkages ($Y_i = Y_j$ and $b_{ji} = b$ for all i, j), this expression simplifies even further to

$$MSR_i = \frac{Y_i}{G_i}(\varphi_1 + \varphi_2) \tag{G.10}$$

We turn next to the marginal private return. Using the expression above for dY,we get $dY'z^* = \varphi_1 Y_i$. The second terms involves dY^*which is

$$dY^* = \sigma \begin{pmatrix} Y_1 & 0 & 0 \\ 0 & Y_2 & 0 \\ 0 & 0 & Y_N \end{pmatrix} \begin{pmatrix} 0 & \omega_{12}^* & \omega_{1N}^* \\ \omega_{21}^* & 0 & \omega_{2N}^* \\ \omega_{N1}^* & \omega_{N2}^* & 0 \end{pmatrix} z^* = \sigma \begin{pmatrix} \omega_{1i}^* Y_1 \\ \omega_{2i}^* Y_2 \\ \omega_{Ni}^* Y_N \end{pmatrix}$$

Recalling that z^{**}denotes an $Nx1$ vector with $+1$ in the i^{th} position and $-s_{ji}$ in the $j \neq i$ positions, we get $dY^{*\prime} z^{**} = -\sigma \sum_{j \neq i} s_{ji} \omega_{ji}^* Y_j$. Combining these results and recalling that $\omega_{ji}^* = \gamma_3 d_{ji}$, the marginal private return for firm i can be written as

$$MPR_i = \varphi_1 \frac{Y_i}{G_i} - \sigma \gamma_3 \sum_{j \neq i} s_{ji} d_{ji} \frac{Y_j}{G_i}.$$

The MPR depends on the coefficient of own R&D in the production function and the coefficient of business stealing in the value equation, plus the product market linkages (these are embedded both in the s_{ji} and d_{ji} coefficients). In the fully symmetric case where all firms are identical in size *and* product market linkages, this simplifies to

$$MPR_i = \frac{Y_i}{G_i}(\varphi_1 - \sigma \gamma_3) \tag{G.11}$$

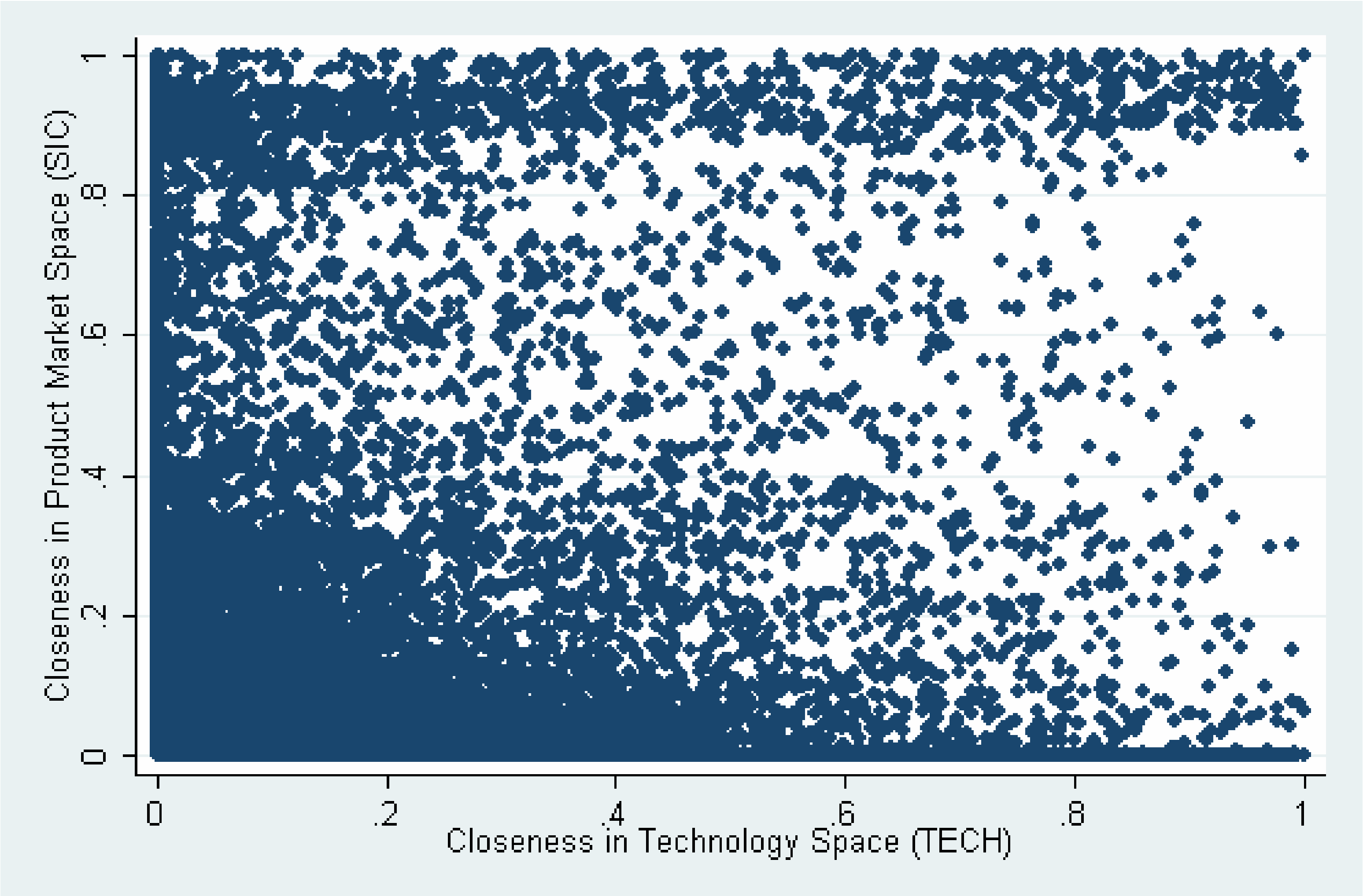
In this fully symmetric case, the ratio between the marginal social and private returns is

$$\frac{MSR}{MPR} = \frac{\varphi_1 + \varphi_2}{\varphi_1 - \sigma\gamma_3} \tag{G.12}$$

The social return is larger than the private return if the coefficient of technology spillovers in the production function is larger than the coefficient of business stealing in the value equation in absolute value, adjusted by σ ($i.e., \varphi_2 > |\sigma\gamma_3|$). In the general case, however, the relative returns also depend on the position of the firm in both the technology and product market spaces.

As we pointed out earlier, in order to compute the private return to R&D in terms of output gains, we need to separate the estimated value effect of R&D into these the output and price effects. The empirical computations of the private returns to R&D are done using the value $\sigma = \frac{1}{2}$. That is, we assume that half of the percentage change in the market value of a firm is due to changes in output and half to changes in its price-cost margin. This assumption can be micro-founded. In particular, we analyzed an N-firm Cournot model with asymmetric costs – where firm i has unit cost c and all other firms have unit cost c'(no cost ranking is assumed). We can show that a marginal increase in R&D by firm i reduces the profit of all other firms, and that *at most half* of this reduction is due to changes in the output levels of those firms. This implies $\sigma \leq \frac{1}{2}$. The actual breakdown into changes in output and price-cost margins depends on the number of firms and the elasticity of demand. Using the assumption $\sigma = \frac{1}{2}$ is conservative in the sense that it provides an upper bound to the MPR, and thus a lower bound to the gap between MSR and MPR when that gap is positive (as we find empirically). Further details are available on http://cep.lse.ac.uk/textonly/_new/research/productivity/BSV_sigma_1March.pdf

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 1: 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	$\partial r_0/\partial r_m$	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 $\varphi_2 = 0$, and technology spillovers correspond to $\varphi_2 > 0$. Strategic complementarity or substitutability between rivals' knowledge stocks is given by the sign of Π_{12}.

TABLE 2: 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	2,006.8	6,494	10,114
Patent flow	P	1	16.2	75
Cite weighted patents		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.

TABLE 3: 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)		(0.105)	(0.192)
Ln($SPILLSIC_{t-1}$)	0.053	-0.083		-0.050	-0.136	-0.235
	(0.007)	(0.032)		(0.031)	(0.031)	(0.109)
Ln(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 Tobin's Q = 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(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 heteroskedacity 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 firms' 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 B3 for details. In column (6) we also control for the firm's own R&D federal and state tax credit values.

TABLE 4: COEFFICIENT ESTIMATES FOR THE CITE-WEIGHTED PATENT EQUATION

Dep Var: Cite weighted Patents	(1)	(2)	(3)	(4)	(5)
Specification:	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin.	Neg. Bin. IV 2^{nd} stage
Distance measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\text{Ln(SPILLTECH)}_{t-1}$	0.518	0.468	0.417	0.530	0.407
	(0.096)	(0.080)	(0.056)	(0.070)	(0.059)
$\text{Ln(SPILLSIC)}_{t-1}$	0.045	0.056	0.043	0.053	0.037
	(0.042)	(0.037)	(0.026)	(0.037)	(0.028)
$\text{Ln(R\&D Stock)}_{t-1}$	0.500	0.222	0.104	0.112	0.071
	(0.048)	(0.053)	(0.039)	(0.039)	(0.020)
Ln(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 1^{st} stage F-tests
$\text{Ln(SPILLTECH)}_{t-1}$					55.3
$\text{Ln(SPILLSIC)}_{t-1}$					15.0
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. Observations	9,023	9,023	9,023	9,023	9,023

Notes: 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. "1^{st} 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 B3 for details.

TABLE 5: COEFFICIENT ESTIMATES FOR THE PRODUCTION FUNCTION

Dep. Var: Ln(sales)	(1)	(2)	(3)	(4)	(5)
Specification:	OLS	OLS	OLS	OLS	IV 2nd Stage
Distance measure	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$\text{Ln(SPILLTECH)}_{t-1}$	-0.022	0.191	0.186	0.264	0.206
	(0.009)	(0.046)	(0.045)	(0.064)	(0.081)
$\text{Ln(SPILLSIC)}_{t-1}$	-0.016	-0.005		-0.007	0.030
	(0.004)	(0.011)		(0.021)	(0.054)
Ln(Capital)_{t-1}	0.288	0.154	0.153	0.156	0.152
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Labor)_{t-1}	0.644	0.636	0.636	0.637	0.639
	(0.012)	(0.015)	(0.015)	(0.015)	(0.016)
$\text{Ln(R\&D Stock)}_{t-1}$	0.061	0.043	0.042	0.043	0.041
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
					First Stage F-Statistic
$\text{Ln(SPILLTECH)}_{t-1}$					112.4
$\text{Ln(SPILLSIC)}_{t-1}$					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 heteroskedacity 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 firms' 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 B3 for details.

TABLE 6: COEFFICIENT ESTIMATES FOR THE R&D EQUATION

Dep Var: Ln(R&D/Sales):	(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(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 heteroskedacity 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 firms' 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 B3 for details. In column (5) we also include the firm's own R&D federal and state tax credit values.

TABLE 7: 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).

TABLE 8: ALTERNATIVE WAYS OF MEASURING SPILLOVERS

A. Baseline (Summarized from Tables 3-6 above)				
	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cites	Real Sales	R&D/Sales
$\text{Ln(SPILLTECH)}_{t-1}$	0.381	0.468	0.191	0.100
	(0.113)	(0.080)	(0.046)	(0.076)
$\text{Ln(SPILLSIC)}_{t-1}$	-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				
$\text{Ln(SPILLTECH}^{EG})_{t-1}$	0.961	0.123	0.179	-0.082
	(0.181)	(0.562)	(0.073)	(0.109)
$\text{Ln(SPILLSIC}^{EG})_{t-1}$	-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				
$\text{Ln(SPILLTECH}^{GEOG})_{t-1}$	1.314	0.037	0.117	
	(0.176)	(0.053)	(0.066)	
$\text{Ln(SPILLTECH)}_{t-1}$	-0.559	0.391	0.101	
	(0.163)	(0.069)	(0.060)	
$\text{Ln(SPILLSIC}^{GEOG})_{t-1}$	0.110			-0.041
	(0.078)			(0.094)
$\text{Ln(SPILLSIC)}_{t-1}$	-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				
$\text{Ln(SPILLTECH}^{J\text{-}COV})_{t-1}$	0.282	0.470	0.141	0.096
	(0.102)	(0.084)	(0.041)	(0.068)
$\text{Ln(SPILLSIC}^{J\text{-}COV})_{t-1}$	-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 3 column (2); patents equation in column (3) corresponds to Table 4 column (2); productivity equation in column (4) corresponds to Table 5 column (2) and R&D equation in column (3) corresponds to Table 6 column (2). In *Panel B* TECH is measured by the coagglomeration 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 sub-section 6.2). The equations all use the preferred specifications from the main tables (i.e. column (1) corresponds to Table 3 column (2); column (2) corresponds to Table 4 column (2); column (3) corresponds to Table 5 column (3) and column (4) corresponds to Table 6 column (2). In *Panel D* we use the same specifications as Panel A except we substitute the Jaffe-Covariance index for both technology ($\text{SPILLTECH}^{J\text{-}COV}$) and product market spillovers ($\text{SPILLSIC}^{J\text{-}COV}$), which is empirically identical to using the Exposure in our log-linear specification with ln(R&D) as an explanatory variable.

TABLE 9: 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
<u>Closeness Measures</u>							
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
<u>Size splits</u>							
4. Largest size quartile	Jaffe	21.1	67.1	46.0	29,700	0.015	0.054
5. Second size quartile	Jaffe	20.4	55.0	34.5	5,900	0.012	0.037
6. Third size quartile	Jaffe	20.7	50.8	30.8	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 non-zero R&D capital stocks. We use our "preferred" systems of equations and coefficients as in Table 7. 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 in 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 (4) Table 7). The second row recalculates this for firms using the Mahalanobis distance measure (column (5) Table 7). The third and fourth rows recalculates this using the Jaffe and Mahalanobis closeness measures with the tax credit instruments for firm-level R&D (columns (6) and (7) Table 7). The next four rows recalculate these figures for firms based on their position in the employment size quartiles.

TABLE 10: DESIRABLE PROPERTIES OF DISTANCE MEASURES

Name	*Definition of $TECH_{ij}$*	**Economic Micro-Foundations**	**Invariance to re-scaling**	**Within Field Overlap**	**Between Field Overlap**	**Non-Overlapping Fields**	**Invariance to aggregation over non-active fields**	**Robustness to aggregation of active Fields**
		EMF	*SCALE*	*WFO*	*BFO*	*NOF*	*AGG*	*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 coagglomeration	$\frac{\sum_\tau (s_{\tau i} - x_\tau)(s_{\tau j} - x_\tau)}{1 - \sum_\tau x_\tau^2}$	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).

APPENDIX TABLES

TABLE A1: AN EXAMPLE OF SPILLTEC AND SPILLSIC FOR FOUR MAJOR FIRMS

	Correlation	*IBM*	*Apple*	*Motorola*	*Intel*
IBM	SIC Compustat	1	0.65	0.01	0.01
	SIC BVD	1	0.55	0.02	0.07
	TECH	***1***	***0.64***	***0.46***	***0.76***
Apple	SIC Compustat		1	0.02	0.00
	SIC BVD		1	0.01	0.03
	TECH		***1***	***0.17***	***0.47***
Motorola	SIC Compustat			1	0.34
	SIC BVD			1	0.47
	TECH			***1***	***0.46***
Intel	SIC Compustat				1
	SIC BVD				1
	TECH				***1***

Notes: The cell entries are the values of $SIC_{ij} = (S_i\ S'_j)/[(S_i\ S_i')^{1/2}(S_j\ S'_j)^{1/2}]$ (in normal script) using the Compustat Line of Business sales breakdown ("SIC Compustat") and the Bureau Van Dijk database ("SIC BVD"), and $TECH_{ij} = (T_i\ T'_j)/[(T_i\ T_i')^{1/2}(T_j\ T'_j)^{1/2}]$ (in ***bold italics***) between these pairs of firms.

TABLE A2: PREDICTING R&D USING FEDERAL AND STATE R&D TAX CREDITS

	(1)	(2)	(3)
Dependent variable:	Ln(R&D)	Ln(R&D)	Ln(R&D)
Ln(State Tax Credit component	-3.828	-4.250	-0.397
of R&D user cost$_{i,t}$)	(0.265)	(0.204)	(0.174)
Ln(Federal Tax Credit component	-1.672	-0.387	-0.440
of R&D user cost$_{i,t}$)	(0.231)	(0.114)	(0.085)
Firm fixed effects	No	Yes	Yes
Year dummies	No	No	Yes
Joint F-test of the tax credits	137.15	304.56	16.28
No. Observations	14,971	14,971	14,971

Notes: Standard errors (in brackets) are robust to arbitrary heteroskedacity and allow for first order serial correlation using the Newey-West procedure.

TABLE A3: ALTERNATIVE CONSTRUCTION OF SPILLOVER VARIABLES

	(1)	(2)	(3)	(4)
A. Baseline (Summarized from Tables 3-6 above)				
Dependent variable	Tobin's Q	Cites	Real Sales	R&D/Sales
$\ln(SPILLTECH)_{t-1}$	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. Constructing SPILLSIC based on BVD industries instead of Compustat				
$\ln(SPILLTECH)_{t-1}$	0.313	0.482	0.100	0.056
	(0.108)	(0.093)	(0.052)	(0.078)
$\ln(SPILLSIC)_{t-1}$	-0.063	0.057	0.000	0.142
	(0.034)	(0.029)	(0.014)	(0.034)
Observations	7,269	6,696	7,364	6,445
C. Alternative Based on SPILLTECH (see Thompson and Fox-Kean, 2005)				
$\ln(SPILLTECH)_{t-1}$	0.105	0.434	0.059	0.023
	(0.062)	(0.054)	(0.025)	(0.029)
$\ln(SPILLSIC)_{t-1}$	-0.063	0.028	0.002	0.021
	(0.033)	(0.039)	(0.013)	(0.019)
Observations	9,848	8,932	9,913	8,386
D. Using firm pairs with (SIC<0.1 and/or TEC<0.1)				
$\ln(SPILLTECH^{*})_{t-1}$	0.135	0.416	0.108	0.044
	(0.109)	(0.070)	(0.044)	(0.073)
$\ln(SPILLSIC^{*})_{t-1}$	-0.060	0.054	0.004	0.093
	(0.032)	(0.036)	(0.012)	(0.033)
Observations	9,944	9,023	9,935	8,579

Notes: Value equation in column (1) corresponds to Table 3 column (2); the patents equation in column (2) corresponds to the Table 4 column (2); the productivity equation in column (4) corresponds to Table 5 column (2) and the R&D equation in column (3) corresponds to the Table 6 column (2). Panel A summarizes results in Tables 3-6. Panel B uses the alternative method of constructing SPILLSIC based on BVD data (see Appendix B.5). Panel C uses a more disaggregated version of technology classes, $SPILLTECH^{TFK}$, as suggested by Thompson and Fox-Kean, 2005). In Panel D TECH and SIC are replaced with the value 0 for any pair of firms in which both TECH and SIC are above 0.1. Otherwise all specifications are the same as in Panel A.

TABLE A4: ECONOMETRIC RESULTS FOR SPECIFIC HIGH TECH INDUSTRIES

A. Computer Hardware

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cite-weighted patents	Real Sales	R&D/Sales
Ln(SPILLTECH)$_{t-1}$	1.884	0.588	0.398	-0.462
	(0.623)	(0.300)	(0.221)	(0.220)
Ln(SPILLSIC)$_{t-1}$	-0.471	0.055	-0.000	0.317
	(0.157)	(0.813)	(0.111)	(0.107)
Observations	358	277	343	395

B. Pharmaceuticals

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cite-weighted patents	Real Sales	R&D/Sales
Ln(SPILLTECH)$_{t-1}$	2.126	1.833	0.981	-0.733
	(0.735)	(0.861)	(0.273)	(0.448)
Ln(SPILLSIC)$_{t-1}$	-1.615	-0.050	-0.669	1.266
	(0.649)	(0.312)	(0.329)	(0.567)
Observations	334	265	313	381

C. Telecommunication Equipment

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cite-weighted patents	Real Sales	R&D/Sales
Ln(SPILLTECH)$_{t-1}$	1.509	1.401	0.789	0.721
	(0.840)	(0.666)	(0.292)	(0.327)
Ln(SPILLSIC)$_{t-1}$	-0.125	0.016	0.095	-0.006
	(0.456)	(0.378)	(0.169)	(0.128)
Observations	405	353	390	450

Notes: Each Panel (A, B, C) contains the results from estimating the model on the specified separate industries (see Appendix B for exact details). Each column corresponds to a separate equation for the industries specified. The regression specification is the most general one used in the pooled regressions. Tobin's Q (column (1)) corresponds to the specification in column (2) of Table 3; Cite-weighted patents (column (2)) correspond to column (2) of Table 4; real sales in column (3) corresponds to column (2) of Table 5; R&D/Sales (column (4)) corresponds to column (2) of Table 6.