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 technological 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 about twice as high as the private returns. We identify the causal effect of R&D by using 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.

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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

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[1]See, for example, Spence (1984), Grossman and Helpman (1991) or Aghion and Howitt (1992). Barro and Sala-i-Martin (2003), Keller (2004), Klenow and Rodriguez-Clare (2004) and Jones (2005) all have recent surveys of the literature.

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, even if there is no econometric bias, 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 under-investment in R&D could be overturned.

This paper develops a methodology to identify the separate effects of technology and product market spillovers and is based on two main features. First, using a general analytical framework we develop the implications of technology and product market spillovers for a range of firm performance indicators (market value, citation-weighted patents, productivity and R&D). The predictions differ across performance indicators, thus providing identification for the technology and product market spillover effects. Second, we empirically distinguish a firm's position in *technology* space and *product market* space using information on the distribution of its patenting across technology fields, and its sales activity across different four-digit industries. This allows us to construct distinct measures of the distance between firms in the technology and product market dimensions[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

[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 com-

of return to R&D, measured in terms of the output gains generated by a marginal increase in R&D. 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 for a twenty year 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 38% and 20%, respectively. At the aggregate level this implies under-investment in R&D, with the socially optimal level being two to three times higher than 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 Federal and State-specific rules) to construct instrumental variables for R&D expenditures. This allows us to estimate the causal impact of R&D on firms own performance and those around it in product and technology space.

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

Our paper has its antecedents in the empirical literature on knowledge spillovers. The dominant approach has been to construct a measure of outside R&D (the "spillover pool")

pete in the semi-conductor market, with little product market competition between the two pairs. Appendix D has more details on this and other examples.

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 follow this idea but extend 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]. We also 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 technologies 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.

The paper is organized as follows. Section 2 outlines our analytical framework. Section 3 describes the data and Section 4 discusses the main econometric issues. The main empirical findings are presented in Section 5, extensions in Section 6, robustness in Section 7 and conclusions in the final section. We also have a series of Appendices with more details on

[4]The same is true for papers that use "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). Our methodology could easily be extended to allow geographic proximity to influence both technological and product market interactions.

the theory (Appendix A), data issues (Appendix B), calculation of the distance measures (Appendix C), examples of firm location (Appendix D), and the methodology for calculating the social and private rates of return to R&D (Appendix E).

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, 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. 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.

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

[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.

(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.[7]

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 $x_m^* = f(k_m, k_0)$. 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[8].

Stage 1

Firm 0 produces innovations with its own R&D, possibly benefiting from 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.[9] Comparative statics yield

$$\frac{\partial r_0^*}{\partial r_\tau} = -\frac{\{\Pi_1\phi_{1\tau} + \Pi_{11}\phi_1\phi_\tau\}}{A} \tag{2.3}$$

[7] 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.

[8] 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. Certainly at $k_m \simeq 0$ this derivative must be negative, as monopoly is more profitable than duopoly.

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

where $A = \Pi_{11}\phi_1^2 + \Pi_1\phi_{11} < 0$ by the second order conditions. If $\phi_{1\tau} > 0$, 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 $\phi_{1\tau} = 0$ or diminishing returns in knowledge production are strong (i.e. $\Pi_1\phi_{1\tau} < -\Pi_{11}\phi_1\phi_\tau$) 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,

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

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).[10]

We also obtain

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

and

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

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 get

$$\begin{aligned}\frac{\partial V^*}{\partial r_\tau} &= \Pi_1\frac{\partial k_0}{\partial r_\tau} \geq 0 \\ \frac{\partial V^*}{\partial r_m} &= \Pi_2\frac{\partial k_m}{\partial r_m} \leq 0\end{aligned}$$

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

[10] 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. Loury, 1979; 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).

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.[11] At the same time, the increase in k_0 raises the level of total factor productivity of the firm, given its R&D spending. The effect of technology spillovers on the firm's R&D decision, however, is ambiguous because it depends on how such spillovers affect the marginal (not the average) product of its R&D and this cannot be signed *a priori* (see equation (2.3)). The same results also hold when there is product market rivalry, regardless of whether it takes the form of strategic complements or substitutes (columns (8) and (9)).

Finally, we note one important caveat regarding the absence of an effect of product market rival R&D on knowledge. Equation (2.6) will only hold if our empirical measure k purely reflects knowledge. As we show formally in Appendix A.3, 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)[12]. 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

[11] 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.

[12] 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).

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

[Table 1 about here]

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[13].

3. Data

In this section we briefly describe the construction of our dataset. Appendix B provides details on the data, and the data and estimation files to replicate all results is available on-line.[14]

3.1. 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"[15].

[13] 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.

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

[15] 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)

The book value of capital is the net stock of property, plant and equipment and employment is the number of employees. R&D is used to create R&D capital stocks calculated using a perpetual inventory method with a 15% depreciation rate (following *inter alia* Hall, Jaffe and Trajtenberg, 2005). So the R&D stock, G, in year t is: $G_t = R_t + (1-\delta)G_{t-1}$ where R is the R&D flow expenditure in year t and $\delta = 0.15$. We use deflated sales as our output measure but also compare this with value added specifications. Industry price deflators were taken from Bartelsman, Becker and Gray (2000) until 1996 and then the BEA four digit NAICS Shipment Price Deflators thereafter. For Tobin's Q, firm value is the sum of the values of common stock, preferred stock and total debt net of current assets. The book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles other than R&D. Tobin's Q was winsorized by setting it to 0.1 for values below 0.1 and at 20 for values above 20 (see Lanjouw and Schankerman, 2004).

3.2. Calculating Technological Closeness

The technology market information is provided by the allocation of all patents by the USPTO into 426 different technology classes (labelled N-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. The technology closeness measure, $TECH_{ij}$ $(i \neq j)$, is also calculated as the uncentered correlation between all firm i, j pairings following Jaffe (1986):

$$TECH_{i,j} = \frac{(T_i T_j')}{(T_i T_i')^{\frac{1}{2}}(T_j T_j')^{\frac{1}{2}}} \tag{3.1}$$

This ranges between zero and one, depending on the degree of overlap in technology, and is symmetric to firm ordering so that $TECH_{ij} = TECH_{ji}$.[16] We construct the pool of technology spillover R&D for firm i in year t, $SPILLTECH_{it}$, as

$$SPILLTECH_{it} = \Sigma_{j,j\neq i} TECH_{ij} G_{jt}. \tag{3.2}$$

where G_{jt} is the stock of R&D.

[16]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.

3.3. Calculating Product Market Closeness

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 industry codes, spanning 762 industries across the sample. We use the average share of sales per industry code 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 of firm i in the four digit industry code k.[17] 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:

$$SIC_{i,j} = \frac{(S_i S_j')}{(S_i S_i')^{\frac{1}{2}}(S_j S_j')^{\frac{1}{2}}} \tag{3.3}$$

This ranges between zero and one, depending on the degree of product market overlap, and is symmetric to firm ordering so that $SIC_{ij} = SIC_{ji}$. We construct the pool of product-market R&D for firm i in year t, $SPILLSIC_{it}$,as:

$$SPILLSIC_{it} = \Sigma_{j,j\neq i} SIC_{ij} G_{jt} \tag{3.4}$$

To control for industry demand shocks, we use a 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 ensures that the $SPILLSIC$ measure is not simply reflecting demand shocks at the industry level. We use a firm-specific measure of industry sales.

3.4. The Mahalanobis distance metric

One drawback of the Jaffe (1986) distance metric in equations (3.1) and (3.3) is that it assumes that spillovers only occur within the same technology class, but rules out spillovers between different classes. This is restrictive because the patent N-classes typically used to describe different technology areas are rather narrow. This assumption, for example, excludes spillovers between the computing N-classes 708 (arithmetic processing and calculating), 709 (multiple computer or process coordinating), 710 (input/output), 711 (memory) and 712 (processing architectures and instruction processing). To address this concern, we develop a new distance

[17] 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).

measure which 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).[18] The idea is that firms will tend to operate across multiple technology classes when these are close to each other, in order to internalize knowledge spillovers. By examining the frequency of co-location of patenting within firms, we can estimate the technology distance between the different classes. Technology classes that are frequently observed within the same firm are judged to be closer than those never observed together. The Mahalanobis measure takes into account the closeness of different firms in technology areas where they both operate, as well as the closeness of their non-overlapping technology areas. The calculation of this Mahalanobis measure, $SPILLTECH^{MAL}$, is notationally quite involved so it presented in Appendix C.1.

We believe this Mahalanobis distance has two advantages over the Jaffe measure. First, it exploits information on the distribution of technology classes within firms to calculate distance between technology classes, and thus improve our measure of the technology distance between firms. Second, it helps to reduce the potential impact of measurement error in the allocation of patents to technology classes. For example, if patent office examiners sometimes erroneously allocate patents in the class "arithmetic processing calculating" to "processing architectures and instruction processing", then our Mahalanobis distance measure would recognize these as closer together and take this into account when generating spillover measures.

A similar distance measure can also be constructed for the distance between firms in product market space, which we call $SPILLSIC^{MAL}$. However, whether this is a better or worse measure of product market distance than the Jaffe measure is less clear. Anti-trust law, for example, restricts the ability of firms in substitutable products to merge, so the within-firm distribution of sales may not tell us so much in aggregate about which sectors are closer to each other.

We present results based on both the Jaffe and Mahalanobis distance metrics in the empirical section. In robustness tests, we also consider several other distance metrics that are based on alternative approaches.

3.5. 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 extent to which the breakdown of firm sales into four digit industries from the Compustat

[18] We wish to thank an anonymous referee for suggesting this approach.

Segment Dataset is reliable.[19] We examine this problem using BVD, an alternative firm-level database to calculate product market closeness. Second, Compustat only contains firms listed on the stock market, so it excludes smaller firms. This is inevitable if one is going to use market value data. Nevertheless, R&D is concentrated in these firms, and our dataset covers the bulk of reported R&D in the U.S. economy. Third, 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 Section 7.3.

3.6. 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 (3.2) and (3.4) 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 (all these correlations are significant at the 1% level). Although these correlations are all positive 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 (mean employment is over 18,000), but with much heterogeneity in size, R&D intensity, patenting activity and market valuation. The two distance measures also differ widely across firms.

[Table 2 about here]

[19] 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 heavily 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 four key endogenous outcome variables: market value, knowledge (measured by citation-weighted patents and total factor productivity) and R&D expenditures.[20] We first discuss the generic issues of identification with all four equations, and then turn to specific problems with each equation.

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})[21]. 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.[22]

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.4, but we sketch the strategy here. The Hall-Jorgenson user cost of capital, ρ_{it}^U is

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

where A_{it} is the discounted value of tax credits and depreciation allowances, τ_{st} 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

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

[21] In calculating robust standard errors we allow the υ_{it}^Q to be heteroskedastic and serially correlated.

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

$[i_t + \delta - \frac{\Delta p_t}{p_{t-1}}]$ does not vary between firms, we focus on the tax price component of the user cost, $\rho^P_{it} = \frac{(1-A_{it})}{(1-\tau_{st})}$.

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".[23] 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".[24]

We use these excluded instruments (and the other exogenous variables) to predict R&D, and then use its predicted value for both the own R&D and 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, whereas the firm's own R&D is instrumented by its own tax prices.

Thirdly, although our baseline models are static, we show that the empirical results are robust to specifications that include a lagged dependent variable.

4.2. Market Value equation

We adopt a simple linearization of the value function proposed by Griliches (1981) augmented with our spillover terms:[25]

$$\ln\left(\frac{V}{A}\right)_{it} = \ln\left(1 + \gamma_1\left(\frac{G}{A}\right)_{it}\right) + \gamma_2 \ln SPILLTECH_{it} + \gamma_3 \ln SPILLSIC_{it} + \gamma_4 X_{2it} + \eta^V_i + \tau^V_t + \upsilon^V_{it} \tag{4.3}$$

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

[23] 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).

[24] 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 for more details.

[25] See also Jaffe (1986), Lanjouw and Schankerman (2004), and Hall et. al. (2005).

imate $\ln\left(1+\gamma_1\left(\frac{G}{A}\right)_{it}\right)$ by a series expansion with higher order terms (denoted by $\phi(\frac{G}{A})$).[26] 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. Thus, the market value equation is:

$$\ln\left(\frac{V}{A}\right)_{it} = \phi((G/A)_{it-1}) + \gamma_2 \ln SPILLTECH_{it-1} + \gamma_3 \ln SPILLSIC_{it-1} + \gamma_4 X_{2it} + \eta_i^V + \tau_t^V + \upsilon_{it}^V \quad (4.4)$$

4.3. Patent Equation

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

$$P_{it} = \exp(\lambda_1 \ln G_{it-1} + \lambda_2 \ln SPILLTECH_{it-1} + \lambda_3 \ln SPILLSIC_{it-1} + \lambda_4 X_{4it} + \eta_i^P + \tau_t^P + \upsilon_{it}^P) \quad (4.5)$$

We use the "pre-sample mean scaling" method of Blundell, Griffith and Van Reenen (1999) to control for fixed effects.[27] This relaxes the strict exogeneity assumption underlying the conditional maximum likelihood 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):

$$\ln Y_{it} = \varphi_1 \ln G_{it-1} + \varphi_2 \ln SPILLTECH_{it-1} + \varphi_3 \ln SPILLSIC_{it-1} + \varphi_4 X_{3it} + \eta_i^Y + \tau_t^Y + \upsilon_{it}^Y \quad (4.6)$$

The key variables in X_{3it} 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

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

[27] 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).

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 prices (as we would expect), the coefficient on $SPILLSIC$ will be negative and the predictions for equation (4.6) are the same as those of the market value equation. Controlling for industry output (see Klette and Griliches, 1996) 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 $SPILLSIC$ is essentially zero once we control for these additional factors.

4.5. R&D equation

We write the R&D intensity equation as:

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

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 instrumental variables in sub-section 6.1. 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

[Tables 3,4,5,6 about here]

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.[28] These are both contrary to the predictions of the theory. When we allow for fixed effects in

[28] 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 since G/A is not "small" - the mean is close to 50% (see Table 2).

column (2), the estimated coefficients on $SPILLTECH$ and $SPILLSIC$ switch signs and are consistent with the theory.[29] 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 2.4% increase in market value and a ten percent increase in $SPILLSIC$ is associated with a 0.7% reduction in market value.

It is also worth noting that, in column (3) when $SPILLSIC$ is omitted the coefficient on $SPILLTECH$ declines and becomes statistically insignificant at the 5 per cent level. The same bias is illustrated for $SPILLSIC$ - if we failed to control for technology spillovers we would find no statistically significant impact of product market rivalry (column (4)). It is only by allowing for both spillovers simultaneously that we are able to identify their individual impacts.[30]

The bias associated with not allowing for fixed effects could arise from various sources. For example, if high $SPILLSIC$ firms are clustered in product market niches with high growth (or expected growth) – where good prospects induce entry and thus greater competition – they will tend to have higher market values.[31] If fixed effects control for this, the true negative effect is revealed. Another possibility is that high $SPILLTECH$ firms may tend to do less marketing, and this will mean that they have lower V/A (as we do not measure goodwill capital). To the extent that goodwill capital does not change much over time, this causes a downward bias on $SPILLTECH$ in column (1) but not in column (2).

In column (5) we re-estimate our results using our Mahalanobis distance measures. We find that the coefficient on $SPILLTECH$ rises three-fold, suggesting that by more accurately weighting distances between technology fields the Mahalanobis spillover metric has substantially reduced attenuation bias. The results for the product market measure in column (5) are also about twice as high.

In the final column we treat R&D as endogenous using R&D tax prices as instrumental variable. The first stage is presented in Appendix Table A2 and shows that the excluded instruments are strong with an F-test of 30. The second stage coefficients on the spillover

[29] The fixed effects are highly jointly significant, with a p-value < 0.001. The Hausman test also rejects the null of random effects plus three digit dummies vs. fixed effects (p-value=0.02).

[30] 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 0.282 (*0.092*) and on $SPILLSIC$ of -0.079 (*0.028*).

[31] This is also indicated by the fact that when we drop both industry sales variables the coefficient on $SPILLSIC$ in column (2) falls from -0.072 to -0.044.

terms in column (6) of Table 3 are correctly signed and significant with magnitudes larger than the baseline column (2)[32].

5.2. Patent Equation

Table 4 presents the estimates for citation-weighted patents equation. Column (1) shows that larger firms and more R&D-intensive firms are more likely to produce highly cited patents. More interestingly, $SPILLTECH$ has a positive and highly significant association with patenting, indicating the presence of technology spillovers. By contrast, the product market rivalry term, $SPILLSIC$, has a much smaller and statistically insignificant coefficient.

In column (2) we control for firm fixed effects by using the Blundell, Griffith and Van Reenen (1999) method of conditioning on the pre-sample, citation-weighted patents [33]. Allowing for fixed effects reduces the coefficient on $SPILLTECH$, but it remains positive and significant[34]. In column (3) of Table 4 we include a lagged dependent variable. There is strong persistence in patenting behavior, as the coefficient is highly significant, 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. The final column treats R&D as endogenous which does not much change the coefficients from column (2).

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

[32] In the market value specification we imposed a coefficient of unity for γ in the equation (4.3) to enable the R&D stock to be included in Tobin's Q rather than as a right hand side variable:

$$\text{Tobin's Q} = \ln\left(\frac{V}{A+G}\right)_{it}$$

Without this, the regression would not be identified given the inclusion of the instruments in the second stage because of their potential direct effect on market value, as well as the impact on R&D stock. In the OLS results the coefficient on γ was 1.14, with the test that $\gamma = 1$ insignificant at the sample-mean (p-value 0.17). Restimating the Tobin's Q regression instead imposing the OLS coefficient of $\gamma = 1.14$ yields similar results, with the coefficient (*standard error*) on $SPILLTECH$ and $SPILLSIC$ as 0.404 (*0.153*) and -0.083 (*0.076*) respectively.

[33] The pre-sample estimator assumes we can capture all of the fixed effect bias by the long pre-sample history of patents (back as far as 1970). To check this assumption, we also included the pre-sample averages of the other independent variables. Since we have a shorter pre-sample history of these we conditioned on the sample which had at least ten years of continuous time series data. Only the pre-sample sales variable was significant at the five per cent level and including this initial condition did not change any of the main results.

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

Note that although the coefficient on $SPILLSIC$ is statistically insignificant and much smaller than $SPILLTECH$ throughout Table 4, it is positive and sometimes significant in robustness tests (see below). In Appendix A3 we present an extended model where patents are endogenously chosen that rationalizes such a positive effect.

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. The negative sign 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 again see a substantial increase (doubling) in the point estimate of the coefficient on technology spillovers. This coefficient on $SPILLTECH$ in the final column which treats R&D as endogenous is similar to the basic specification of column (2)[35]

One might be concerned that there 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.[36] We also experimented with using an estimate of value added instead of sales as the dependent variable, which led to a similar pattern of

[35] The coefficient on $SPILLSIC$ is negative and significant which may indicate that there is still some residual firm-specific price variation in the dependent variable. R&D by product market rivals will depress prices and this may be reflected in the negative coefficient.

[36] $SPILLTECH$ took a coefficient of 0.101 and a standard error of 0.046 and $SPILLSIC$ remained insignificant (coefficient of 0.008 and a standard error of 0.012). Including a full set of two digit industry time trends also lead to the same findings. The coefficient (*standard error*) on $SPILLTECH$ was 0.093 (*0.048*).

results.[37]

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.[38] In column (3) we include a lagged dependent variable.[39] Column (4) uses the Mahalanobis distance measures and column (5) treats R&D as endogenous. In both specifications we find that $SPILLSIC$ remains positive, but it is insignificant in the final column. This suggests that the significance of $SPILLSIC$ in the OLS regressions may be due to common R&D shocks rather than strategic complementarities. The coefficient on $SPILLTECH$, which is theoretically of ambiguous sign, is not robust. It is insignificant in columns (2) and (3), positive and significant in columns (1) and (5), 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.[40] However, treating R&D as endogenous (as we do in the final column), weakens this conclusion as it suggests that the positive covariance of own R&D and $SPILLSIC$ may be driven by common shocks.

5.5. Summary of basic empirical results

Table 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

[37] 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*). 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*).

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

[39] 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. We used lagged instruments dated t-2 to t-8 in the differenced equation and lagged differences dated t-1 in the levels equations. In the most general dynamic specification of column (3) the coefficient (*standard error*) on $SPILLSIC$ was 0.140 (*0.023*) and the coefficient (*standard error*) on $SPILLTECH$ was -0.026 (*0.018*). Since the lagged dependent variable took a coefficent of 0.640(0.046) this implies a larger magnitude of the effect of $SPILLSIC$ on R&D than the main within group specifications. Note that the instruments were valid at the five per cent level according to the Hansen-Sargan test.

[40] 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.

by the data. This holds true whether we use the Jaffe or Mahalanobis version of technology and product market distance and whether or not we treat R&D as endogenous. 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 generally no effect on patents or TFP.

[**Table 7 about here**]

6. Extensions: Industry Heterogeneity and Private vs. Social Returns to R&D

In this section we present two major extensions to our empirical investigations. First, we estimate our model on three major high tech sectors to examine how the strength of technology spillovers and product market rivalry varies across sectors. Second, 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.

[**Table 8 about here**]

6.1. Econometric results for three high-tech industries

We have used both the cross-firm and cross-industry variation (over time) to identify the technology spillover and product market rivalry 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. Table 8 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.[41] 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, the coefficients (*standard error*) on $SPILLTEC$ and $SPILLSIC$ in the market value equation for computer hardware are 2.314 (*0.668*) and -0.512 (*0.243*) respectively.[42]

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. However, there is also substantial heterogeneity across the sectors. First, the size of the technology spillover and product market rivalry effects vary (we use these differences in the computation of the returns to R&D in the next sub-section). 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.

[Table 9 about here]

[41] Austin (1993) also found evidence of rivalry effects through the market value impact of pharmaceutical patenting. See also Klock and Megna (1993) on semi-conductors.

[42] 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.

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

6.2.1. 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.[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 E provides a detailed discussion of how to calculate these rates of return for individual firms within our analytical framework. In the general case, the rates of return for individual firms depend on the details of their linkages to other firms in both the technology and product market spaces. Although we will use the general 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 as

$$MSR = (\frac{Y}{G})(\varphi_1 + \varphi_2) \tag{6.1}$$

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

[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 (for a thoughtful discussion of these issues, see Griliches, 1979).

Y/G is the ratio of output to the R&D stock.[44] In this formulation the MSR is simply the marginal product of R&D, which reflects both the contribution to the firm's own R&D stock and to the stock of technology spillovers enjoyed by 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 is

$$MPR = (\frac{Y}{G})(\varphi_1 - \sigma\gamma_3) \tag{6.2}$$

In equation (6.2) 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]

In this symmetric case with no amplification, 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 the firm in both the technology and product market spaces.

6.2.2. 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 38.7% ($= 2.48 * (0.045 + 0.111)$), and an estimate of the MPR of 20.1% ($= 2.48 * (0.045 + 0.036)$). This calculation shows that, for the whole of sample of firms taken

[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] 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 E 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.

together, the marginal social returns are approximately double 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, η (i.e. let $R = r^{\eta}$ where R is the level of R&D and r is the marginal return). Our estimated coefficients on the tax credit variables from the first stage IV regression (column (1), 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. Using these values, and the ratio of MSR to MPR of 1.92, we find that the socially optimal level of R&D is about twice as large as the observed level (between 1.7 and 2.4) [46]

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 38.1% and the gross private returns at 20.0%, again indicating a substantial divergence between social and private returns of 18.1 percentage points. This is surprisingly similar to the results for the symmetric no amplification case discussed above, suggesting that the simple case is not misleading when considering the aggregate effects. Second, row 2 in Table 9 shows the results from using the Mahalanobis distance metric, in which gross social returns are shown to be 34 percentage points above private returns. Row 3 shows the IV results which shows the smallest rates of private and social return, mainly because the coefficient on own R&D in the production function is about half that of the OLS estimate. Even here, however, 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

[46] These figures are similar to those estimated from macro data in an endogenous growth model framework by Jones and Williams (1998). They report social returns to R&D of about 2 to 4 times private returns. Our *gross* ratio of MSR to MPR is 1.92 (= 38.7/20.1) for the fully symmetric case without amplification. If we assumed a 15% depreciation of social and private R&D stock, we would get a ratio of *net* MSR to MPR of 4.65 (= (38.7-15)/(20.1-15)). Jones and Williams (1998) also estimate the social optimal level of R&D to be about four times larger than the observed level.

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 cannot inform on this important 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.

Third, in rows 8-10 we present the returns to R&D for the three high-tech industries examined in sub-section 6.1. On average, the firms in all three high-tech sectors have higher private and social returns to R&D than the sample average. These higher returns are the result of the larger own R&D and spillover R&D coefficients which we found for these industries, as reported in Table 8. These high private returns initially look surprising, given firms can freely invest in R&D to drive their private returns down to their risk-adjusted cost of capital. However, in these high-tech industries the rates of depreciation of R&D and the risks of R&D are both likely to be higher due to more rapid rates of technological progress, and this increases the required gross private returns to R&D. It is also true that real R&D per firm is rising rapidly in these industries over our sample period (9.3% per year, on average), so that short-run adjustment costs may also push up the short-run private returns to R&D.

One striking feature of our high-tech industry results is that for pharmaceutical firms the private and social returns to R&D are roughly equal. The reason for this is the high levels of business stealing estimated for pharmaceutical R&D. We find that more than 80% of the private returns to R&D for pharmaceutical firms comes from the business stealing effect. Part

[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 this strong business stealing may reflect imitative research strategies whereby firms replicate the therapeutic properties of a competitor's existing, patented drug with a slightly modified chemical entity.[48] Of course, incremental research is not limited to this sector, but it may be that such strategies are more effective in redistributing profit in pharmaceuticals than in other industries where technologies are made up of a multitude of patented components.

One important caveat is that our estimates of the social returns are based on the increases in output from the R&D, and thus may not fully capture the consumer surplus generated. These gains in consumer surplus are possibly a more important component of the total social returns (health benefits) for drugs than for other sectors.[49]

Overall, our results show clearly that there is substantial variation across industries in the strength of the business stealing and technology spillover effects, and this provides some support for thinking about more targeted R&D tax credits which our methodology helps to identify. Of course, in any such assessment the dangers of rent-seeking behavior that often accompanies targeted policies must be taken seriously.

7. Robustness

We have considered a wide range of robustness tests and report three of the most important here: an alternative to the Compustat Segment Data, alternative distance metrics and disaggregating patent classes.

7.1. An Alternative to 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 cross-sectional industry and ownership information on about ten million establishments in North America and Europe, which can be directly matched into Compustat to create a breakdown of each firm's activity across four digit industries. The correlation between the Compustat

[48] While this claim of "me-too" research is widespread among critics of this industry, we are not aware of any systematic studies that document this phenomenon. It is also important to bear in mind that even small changes in drug compounds can make big differences in the side effects of drugs, which of course also have social value.

[49] It might be thought that the small divergence between social and private returns reflects the importance and effectiveness of patent protection in pharmaceuticals, allowing firms to appropriate most of the social surplus from their new drugs. But this interpretation is contradicted by the fact that we estimate large technology spillover effects in both the production function and market value equations for pharmaceutical firms, which should not be observed if firms fully appropriated the returns to their R&D.

Segment and BVD Dataset measures is reasonably high. For example, the within-firm correlation of $\ln(SPILLSIC)$ across the Compustat Segment and BVD datasets is 0.737 (the within-firm variation identifies our empirical results, as we control for fixed effects). The empirical results (see Appendix Table A3) are also remarkably similar to the earlier tables. In the market value equation, the estimated impact of $SPILLTECH$ is positive and $SPILLSIC$ is negative, and both are statistically significant. In the patents equation, the coefficients on $SPILLTECH$ and $SPILLSIC$ are both positive and significant. In the productivity equation, $SPILLTECH$ is positive and significant, and in the R&D regression, $SPILLSIC$ is positive and significant. These results confirm the key findings of technology spillovers, product market rivalry and strategic complementarity of R&D.

7.2. Alternative distance metrics

One unattractive feature of the Jaffe version of the distance metric, SIC_{ij}, is that the distance measure between firm i and firm j is not invariant with respect to firm j's sales in a third sector where firm i does not operate. We consider an alternative distance measure, $SIC^A_{i,j} = S_i S_j'$, that is robust to this problem and can also be rationalized by a simple model of independent product markets coupled with aggregation (see Appendix C.2). In this case the alternative product market spillover measure is $SPILLSIC^A_{it} = \Sigma_{j \neq i} SIC^A_{ij} G_{jt}$. (The analogous measure for technology spillovers is $TECH^A_{i,j} = T_i T_j'$ and $SPILLTECH^A_{it} = \Sigma_{j \neq i} TECH^A_{ij} G_{jt}$ where T_i is the vector of firm i's patenting distribution across technology fields.) However, this alternative measure also has important disadvantages compared to the Jaffe measure. Most importantly, it is sensitive to arbitrary industry boundaries that affect overlap in sales distributions. Reassuringly, our empirical results using this alternative measure of distance are very similar to those using our baseline measure (Panels A-C in Table A4 present the comparative results using a consistent sample).[50]

7.3. 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

[50] We also considered a third alternative, based on Ellison and Glaeser's (1997) measure of "co-agglomeration". The empirical results were qualitatively similar to those from our baseline specification (for details, see Bloom, Schankerman and Van Reenen, 2007).

as the classification is subject to a greater degree of measurement error.[51] Nonetheless, to check robustness, we reconstructed the (Jaffe) distance metric using six digit patent classes, $TECH_{it}^{TFK}$, and then used that measure to construct a new pool of technology spillovers, $SPILLTECH_{it}^{TFK}$. The empirical results are robust for all four of the equations (see Panel D in Table A).

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 about 18 percentage points larger than the the private return. So at the aggregate level this implies under-investment in R&D, with the socially optimal level being about twice 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.

Looking across different high tech industries broadly supports the main "macro" findings when we pool across all sectors. However, we do find evidence for strategic complementarity in computers and pharmaceuticals (but not telecommunications equipment) which is somewhat disguised in the pooled sample. Furthermore, we also find that the business stealing effect in the pharmaceutical sector is particularly strong, sufficient to make their private returns to R&D roughly equal to the social returns.

[51] 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.

There are various extensions to this line of research. First, while we examined heterogeneity across industries by looking at three high-tech sectors, 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. In addition, one might exploit more detailed industry-specific datasets to study this phenomenon in the context of a structural model. Third, the semi-parametric approaches in Pinske, Slade and Brett (2002) could be used to construct alternative spillover measures. Finally, it would be interesting to investigate how geographic distance shapes both technology and product market spillovers, which could potentially be undertaken by using data on the geographic location of subsidiaries and patenting activity (see Lychagin et al, 2010).

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 rarely subjected to rigorous empirical testing.

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Appendices

A. Generalizations of the 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

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

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

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 θ_{ij} and ω_{ij} (i.e. we assume that $\frac{\partial \pi^*}{\partial r_j}$can be summarized in the form $\pi_2^i \omega_{ij} + \pi_3^i \theta_{ij}$ 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 $dr_{im} = \sum_{s \in S} \theta_{is} dr_s = 0$. These changes imply some change in the technology spillovers $dr_{i\tau} = \sum\limits_{s \in S} \omega_{is} dr_s$, which in general will differ from zero (it can be either positive or negative depending on the ω and θ weights). Now totally differentiate the first order condition, allowing only r_s for $s \in S$ to change.[52] This gives

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

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.

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

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

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

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 $dr_{i\tau} = \sum_{s \in S} \omega_{is} dr_s$. 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) $F = \pi^0(f(1,0), f(0,1); k_0 = 1) - \pi^0(f(0,1), f(1,0); k_0 = 0)$. The expected value of firm 1 can be expressed as

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

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 $hF - R \geq 0$ (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

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

Imposing symmetry and using comparative statics, we obtain

$$\begin{aligned} sign\left(\frac{\partial r_0}{\partial r_m}\right) &= sign\{h_{12}(hF(n-1) + rF - R\} + \{h_1(n-1)(h_1F - 1)\} \\ &\quad -\{h_{22}(n-1)(hF - R)\} - h_2\{(n-1)h_2F - 1\}\} \end{aligned}$$

We assume $h_{12} \geq 0$ (spillovers do not reduce the marginal product of a firm's R&D) and $h_1 F - 1 \geq 0$ (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 $(n-1)h_2 F - 1 \leq 0$. 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.[53].

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 $x_0^* = f(\theta_0 k_0, \theta_m k_m)$ 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

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

[53] 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.

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:[54]

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

where $V_{r_0 r_\tau} \equiv \frac{\partial^2 V}{\partial r_0 r_\tau}$,etc.

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 $V_{r_0r_0} < 0, V_{\rho_0\rho_0} < 0, V_{\rho_0 r_0} > 0$ (provided Π_{11} is 'sufficiently small') and $A = V_{r_0r_0}V_{\rho_0\rho_0} - V_{r_0\rho_0}^2 > 0$ by the second order conditions, and the other cross partials: $V_{r_0r_\tau} = \frac{\phi_{12}}{\phi_1} + \theta_0^2\phi_1^0\phi_2^0\Pi_{11}; V_{r_0r_m} = \theta_0\theta_m\phi_1^0\phi_1^m\Pi_{12}, V_{r_0\rho_\tau} = 0; V_{r_0\rho_m} = (\lambda-1)\theta_0 k_m\phi_1^0\Pi_{12}$;

$V_{\rho_0 r_\tau} = (\lambda-1)\theta_0 k_0\phi_2^0\Pi_{11}; V_{\rho_0 r_m} = (\lambda-1)k_0\theta_m\phi_1^m\Pi_{12}; V_{\rho_0\rho_\tau} = 0$; 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 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

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

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.[55]

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[56], 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 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

[55] 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.

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

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. Instrumental Variables

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.

$$\ln Y_{it} = \beta_1 \ln R_{it} + \beta_2 \ln(\Sigma_{j \neq i} TECH_{ij} R_{jt}) + u_{it} \tag{B.1}$$

We are concerned that $E(u_{it}\ln R_{it}) \neq 0$ and $E(u_{it}\ln R_{jt}) \neq 0$, so OLS is inconsistent, and consider instrumental variable techniques. Note that R&D is a persistent series, is 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. Tax-prices for R&D are natural instruments to consider as they should effect the amount of R&D performed through the R&D factor demand equation, but should have no direct impact on productivity conditional on R&D itself. Intuitively, the coefficient on R_{it} is identified by variation in its own tax-price and the coefficient on $SPILLTECH$ is identified from variation in the tax-prices facing other firms.

The Hall-Jorgenson user cost of capital, ρ_{it}^U is

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

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

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[57].

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

$$\rho_{it}^{S} = \sum_{s} \theta_{ist} \rho_{st}^{S}$$

where ρ_{st}^{S} is the state level tax price (from ‘, 2009) 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 (B.2).

The instruments can all be used for the production function and patents equation. For the R&D equation, the instruments need to be directly in the second stage. The coefficients on the spillover variables are therefore identified from the instruments using other firms' values of the R&D tax price.

We implement the IV approach described here by projecting the endogenous variable (R&D) on the instruments in the first stage (e.g. column (1) of Table A2), calculating the predicted values and then plugging these into a second stage estimation procedure. We correct the standard errors using 1,000 bootstrap replications over firms. The alternative approach of straightforward two stage least squares using the distance-weighted versions of the tax-prices as instruments for spillovers is infeasible because the panel is unbalanced. Consequently 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 $SPILLTECH_{i,t}$ 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_{it}^{F} for firm j are zero per entry (since they are missing) but strictly positive post entry.

[57] 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.

One might be concerned that the current values of the instruments are not exogenous so we also conducted experiments lagging the tax-credit instruments one and two periods. These led to qualitatively similar results.

B.4. Specific High Tech Industry Breakdown

In Table 12 the industries we consider are the following. *Computer hardware* in Panel A 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* in Panel B 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).

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

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.5.1. 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.5.2. 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

Some general issues regarding construction of spillover measures are discussed in section 3. We have shown results using both the Jaffe (1986) and Mahalanobis distance metrics, but there is obviously a host of alternatives. To highlight the issues, consider a general form of the relationship between an outcome measure Q_i (e.g. the market value of firm i) and product market spillovers from other firms in the economy (for notational simplicity we abstract from other factors, including technology spillovers, to which a similar argument applies):

$$Q_i = g(S_i, \mathbf{S}_j, R_j; \boldsymbol{\theta}) \tag{C.1}$$

where S_i is a vector of firm i's sales distribution across industries, $\mathbf{S}_j$ is the matrix of all other firms' sales distribution vectors, R_j is the vector of R&D for each firm j, $\boldsymbol{\theta}$ is a parameter vector and $g(.)$ is an unknown function that maps sales distributions and R&D to firm i's outcome. Different assumptions over the functional form of $g(.)$ will define the product market spillover relationship. The only substantive assumption we have made in equation (C.1) is that firm sales are the relevant measure of where companies are located in product market space. Empirically, we have to place more structure on equation (C.1) to operationalize it in our application. Pinske, Slade and Brett (2002) discuss general issues in constructing semi-parametric versions of equation (C.1). Our approach in this paper is to consider several possible parametric versions.

C.1. Mahalanobis

To explain the calculation of the Mahalanobis normed measure we need to define some notation. First, the $(N, 426)$ matrix $T = [T_1', T_2'...T_N']$ which contains in each row firms' patent shares in the 426 technological classes. Second, we define a normalized $(N, 426)$ matrix $\widetilde{T} = [T_1'/(T_1T_1')^{\frac{1}{2}}, T_2'/(T_2T_2')^{\frac{1}{2}}...T_N'/(T_NT_N')^{\frac{1}{2}}]$, in which each row is simply normalized by the firm's patent share dot product. Third, we define the (N, N) matrix $TECH = \widetilde{T}\widetilde{T}'$. This matrix $TECH$ is just the standard Jaffe (1986) uncentered correlation measure between firms i and j, in which each element is the measure $TECH_{i,j}$, exactly as defined in (3.1) above. Fourth, we define a $(426, N)$ matrix $\widetilde{X} = [T_{(:,1)}'/(T_{(:,1)}'T_{(:,1)})^{\frac{1}{2}}...T_{(:,N)}'/(T_{(:,N)}'T_{(:,N)})^{\frac{1}{2}}]$ where $T_{(:,i)}$ is the i^{th} column of T. This matrix $\widetilde{X}$ is similar to $\widetilde{T}$, except it is the normalized share of 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) 0 to 1 uncentered correlation measure between patent classes (rather than between firms). So, for example, if patent classes i and j coincide frequently within the same firm, then $\Omega_{i,j}$ will be close to 1 (with $\Omega_{i,i} = 1$), while if they never coincide within the same firm $\Omega_{i,j}$ will be 0.

The Mahalanobis normed technology closeness measure is defined as $TECH^{MAL} = \widetilde{T}\Omega\widetilde{T}'$. 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 $TECH^{MAL} = TECH$. 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.

C.2. Model-based $SPILLSIC^A$

Consider a relationship between Tobin's Q, Q_i^l (this could be any performance outcome, of course) for firm i which operates in industry l (l = 1,...., L). We abstract away from other covariates (including $SPILLTECH$ and the firm's own R&D) for notational simplicity. Strategic interaction in the product market means that Q_i^l is affected by the R&D of other firms in industry l. Part of each rival firm's total R&D across all the industries it operates in, r_j, is "assigned" to a particular industry l and will influence Q_i^l. R&D is not broken down by industry l at the firm level in any publicly available dataset that we know of. Consider the equation:

$$Q_i^l = \alpha \sum_{j,j\neq i} \omega_j^l r_j \tag{C.2}$$

where the weights ω_j^l determine the part of firm j's total R&D that is assigned to industry l (we discuss what these weights might be below). Next, note that industry-specific information does not exist for Q_i^l (market value is a company level measure and is not industry-specific). Consequently we have to aggregate across the industries in which firm i operates:

$$Q_i \equiv \alpha \sum_l h_i^l Q_i^l = \alpha \sum_l h_i^l \sum_{j,j\neq i} \omega_j^l r_j \tag{C.3}$$

where h_i^l are the appropriate aggregation weights. Substituting (C.3) into (C.2) gives

$$Q_i = \alpha \sum_{j,j\neq i} \sum_{l} h_i^l \omega_j^l r_j \tag{C.4}$$

We write this compactly as:

$$Q_i = \alpha \sum_{j,j\neq i} d_{ij} r_j \tag{C.5}$$

where d_{ij} is the distance metric between firm i and firm j which will depend on the weights h_i^l and ω_j^l. Different approaches to these weights give the different empirical measures of the distance metrics, and thus different measures of $SPILLSIC$.

For the weight on h_i^l it seems natural to use the share of firm's total sales (s_i^l) in an industry l as the weight. Theoretically, Q_i^l is the ratio of the firm's market value to its capital assets (V/A) of firm i at the industry level and we observe the weighted sum (summing across all "industry V's" and "industry A's" at the parent firm level). If we knew the firm's industry-specific value (V) and capital (A) then we would have better weights, but these are unobservable.

The weights, ω_j^l, are far more difficult to determine as they represent the "assignment" of rival R&D to a specific industry. Under the baseline method in this paper we assume that d_{ij} is the uncentered correlation coefficient as in Jaffe (1986) except using the sales distribution across four digit industries. This is $SPILLSIC$ so:

$$Q_i = \alpha SPILLSIC_i \tag{C.6}$$

The use of the uncentered correlation could be considered *ad hoc*, so alternatively consider $\omega_j^l = s_j^l$, the share of firm j's sales in industry l. One justification for this procedure is that what matters is total rival R&D in industry l. If a firm's R&D intensities across industries are similar then using sales weights correctly estimates the R&D of firm j in industry l. An alternative justification is that firm i does not know in which industry firm j's R&D will generate innovations (indeed firm j may also not know). Under this assumption using equation (C.4) we then obtain, $SPILLSIC_i^A$

$$SPILLSIC_i^A = \sum_{j,j\neq i} \left(\sum_{l} s_i^l s_j^l \right) r_j = \sum_{j,j\neq i} SIC_{ij}^A r_j \tag{C.7}$$

Note that SIC_i^A is the numerator in the Jaffe-based measure. The results from using $SPILLSIC_i^A$ (and the analogous $SPILLTECH_i^A$) as an alternative measure are contained in Table A4 Panels B and C. The results are robust to this experiment.

D. Case Studies of particular firms location in technology and product space

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. Computing Private and Social Returns to R&D

E.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 E.2 provides some basic notation and derives some "reduced forms" after substituting out all the interactions operating through the spillover terms. The main results are in sub-section E.3. which calculates the general form of the marginal social and private returns to R&D to an arbitrary firm. Aggregating over all firms, we then show that much of the intuition for what drives the expression can be seen in a special case where there is no amplification (due to the presence of spillovers in the R&D equation) and when firms are symmetric. 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 as φ_2 is larger and private returns will be larger as (the absolute value of) γ_3 rises. Both terms increase in the effect of R&D on output (φ_1).

E.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 $R_{it} = R_{it-1}$, $Y_{it} = Y_{it-1}$ 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

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

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

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

where V/A is Tobin's Q, and X_1, X_2 and X_3 are vectors of control variables (for ease of exposition we treat them as scalars). We then solve out the cross equation links with Y_{it} by substituting equation (E.3) into equations (E.1). This yields a new equation for R&D:

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

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 (E.4), (E.2) and (E.3).

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

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

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 $g^i = \ln[\sum_{j\neq i} SIC_{ij} G_j]$.By similar steps

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

Using these approximations, we can write the R&D equation (E.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

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

where $\Omega = I - H$.

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

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

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

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

Finally, the market value equation can be expressed as

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

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:

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

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

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

E.3.1. General Case

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 set $d \ln R_i = \alpha_4' dX_{1i} = 1$ and zero for $j \neq i$.[58] Using the R&D equation (E.5), the absolute changes in R&D levels, after amplification, are given by the $Nx1$ vector $dG = B_G \Omega^{-1} i^*$, where i^* is an $Nx1$ vector

[58] Note we scale by 100 here (one percent is taken as 1). In the final calculations the change in R&D stock must be divided by 100.

with one in the i^{th} position and zeroes elsewhere, and B_G is an NxN matrix with R_i in the i^{th} diagonal position and zeroes elsewhere. From the production function (E.6), this induces changes in productivity (output, given the levels of labor and capital) which are given by $dY = B_Y M\Omega^{-1}i^*$, where B_Y denotes an NxN matrix with Y_j in the j^{th} diagonal position $(j = 1, ..., N)$ and zeroes elsewhere.

The *marginal social return* to a dollar of R&D by firm i is given by the total output gain due to the increase in productivity divided by the total increase in the stock of R&D:

$$MSR_i = \frac{dY'i}{dG'i} \tag{E.8}$$

where i' is a $1xN$ vector of ones. Note that the MSR is a scalar.

The *marginal private return* to R&D 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 $i^{*\prime}dY$. 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.

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 (E.7), the induced percentage change in market value is

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

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. 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 $SPILLSIC$). Then we can write the absolute output changes associated with business stealing as $dY^* = \sigma B_Y \Gamma^* \Omega^{-1} i^*$.

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^*).

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, call it s_{ji}, depends the closeness of the two firms, SIC_{ji}, and on how much firm i changes its R&D stock, which is what induces the redistribution, dG_i. Following our earlier derivation of the linear approximation to the system, we use

$$s_{ji} = \frac{SIC_{ji} dG_i}{\sum_{k \neq j} SIC_{jk} dG_k}$$

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

Let i^{**}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 $dY'i^* + dY^{*\prime}i^{**}$. 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 :

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

A comparison of the expressions for MSR and MPR, in equations (E.8) and (E.9), shows that we cannot say which is larger *a priori*. The social return is larger because it includes productivity (output) gains from firms other than i due to technology spillovers, but it also counts the full R&D costs of other firms (if there is amplification), which makes it smaller. Moreover, the private return counts business stealing effects, which makes it larger than the social return which excludes them.

E.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:

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

It follows that $dY'i = \varphi_1 Y_i + \sum_{j \neq i} \delta_{ji} Y_j$, so the marginal social return for firm i can be expressed as

$$MSR_i = \varphi_1 \frac{Y_i}{G_i} + \varphi_2 \sum_{j \neq i} b_{ji} \frac{Y_j}{G_i}.$$

The MSR depends on the coefficients of own R&D and technology spillovers in the production function, and the technology spillover linkages across firms. 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 expressions simplifies to

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

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

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

Recalling that i^{**}denotes an $Nx1$ vector with $+1$ in the i^{th} position and $-s_{ji}$ in the $j \neq i$ positions, we get $dY^{*\prime}i^{**} = -\sigma \sum_{j \neq i} s_{ji} \omega^*_{ji} Y_j$. 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 becomes

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

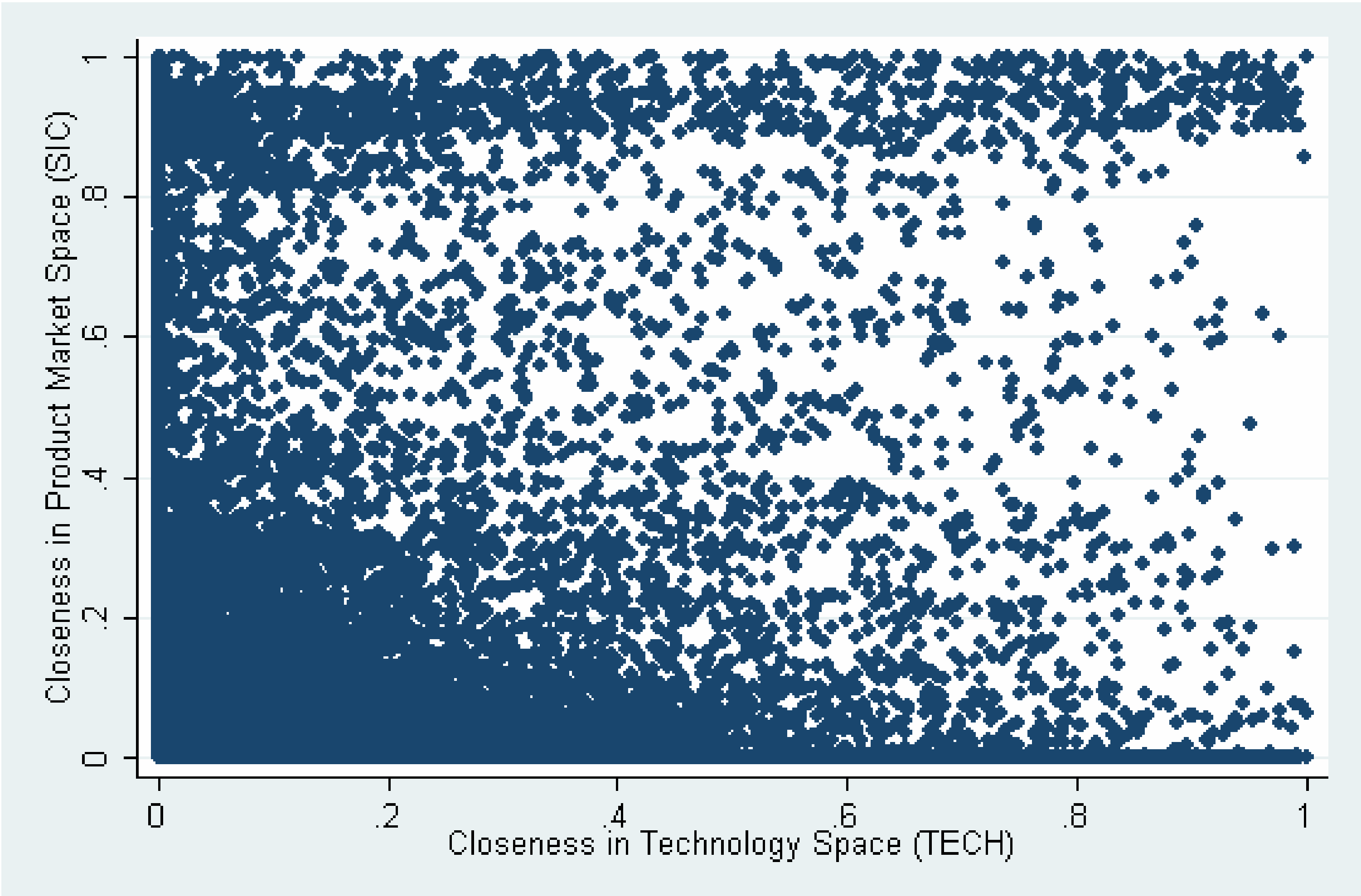
In this fully symmetric case, the ratio between the marginal social and private returns is

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

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.

The empirical computations of the private returns to R&D are done using $\sigma = \frac{1}{2}$. 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

Equation	Comparative static prediction	Empirical counterpart	**No Technology Spillovers**			**Technology Spillovers**		
			No Product Market Rivalry	Strategic Complements	Strategic Substitutes	No Product Market Rivalry	Strategic Complements	Strategic Substitutes
Market value	$\partial\Pi_0/\partial r_\tau$	Market value with SPILLTECH	Zero	Zero	Zero	Positive	Positive	Positive
Market value	$\partial\Pi_0/\partial r_m$	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

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	17,914	22,419	17,944
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)
R&D treated as:	Exogenous	Exogenous	Exogenous	Exogenous	Exogenous	Endogenous
Distance measure:	Jaffe	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
Ln($SPILLTECH_{t-1}$)	-0.042	0.242	0.186		0.903	0.579
	(0.012)	(0.105)	(0.100)		(0.105)	(0.124)
Ln($SPILLSIC_{t-1}$)	0.051	-0.072		-0.050	-0.136	-0.087
	(0.007)	(0.032)		(0.031)	(0.031)	(0.033)
Ln(R&D Stock/Capital	0.842	0.799	0.794	0.799	0.835	
Stock)$_{t-1}$	(0.154)	(0.197)	(0.198)	(0.198)	(0.198)	
Firm fixed effects	No	Yes	Yes	Yes	Yes	Yes
No. Observations	9,944	9,944	9,944	9,944	9,944	9,926

Notes: Dependent variable in columns (1) to (5) is Tobin's Q = V/A is defined as the market value of equity plus debt, divided by the stock of fixed capital. In column (6) the dependent variable is Tobin's Q including R&D = (V+G)/A where G is the stock of R&D. This specification avoids including an endogenous right hand side variable – see Section 4 and Appendix Sub-section B4 for details. 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.

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

	(1)	(2)	(3)	(4)	(5)
R&D treated as:	Exogenous	Exogenous	Exogenous	Exogenous	Endogenous
Distance measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$Ln(SPILLTECH)_{t-1}$	0.438	0.423	0.375	0.583	0.302
	(0.085)	(0.071)	(0.050)	(0.100)	(0.071)
$Ln(SPILLSIC)_{t-1}$	0.043	0.053	0.041	0.079	0.076
	(0.042)	(0.036)	(0.026)	(0.050)	(0.049)
$Ln(R\&D\ Stock)_{t-1}$	0.507	0.221	0.104	0.234	0.289
	(0.048)	(0.053)	(0.039)	(0.052)	(0.047)
$Ln(Patents)_{t-1}$			0.420		
			(0.020)		
Pre-sample fixed effect		0.547	0.299	0.523	0.551
		(0.046)	(0.033)	(0.046)	(0.036)
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. Observations	9,023	9,023	9,023	9,023	8,602

Notes: Estimation is conducted using the Negative Binomial model. Standard errors (in brackets) are robust to arbitrary heteroskedacity and 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)). The fixed effects in column (3) are estimated through the "pre-sample mean scaling approach" of Blundell, Griffith and Van Reenen (1999) – see text.

TABLE 5 –
COEFFICIENT ESTIMATES FOR THE PRODUCTION FUNCTION

	(1)	(2)	(3)	(4)	(5)
R&D treated as:	Exogenous	Exogenous	Exogenous	Exogenous	Endogenous
Distance measure	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
Ln(SPILLTECH) $_{t-1}$	-0.030	0.103	0.111	0.212	0.078
	(0.009)	(0.046)	(0.045)	(0.068)	(0.033)
Ln(SPILLSIC) $_{t-1}$	-0.016	0.010		0.015	-0.017
	(0.004)	(0.012)		(0.023)	(0.012)
Ln(Capital) $_{t-1}$	0.286	0.161	0.161	0.163	0.156
	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Ln(Labor) $_{t-1}$	0.650	0.631	0.631	0.634	0.648
	(0.012)	(0.015)	(0.015)	(0.015)	(0.015)
Ln(R&D Stock) $_{t-1}$	0.059	0.044	0.045	0.044	0.019
	(0.005)	(0.007)	(0.007)	(0.007)	(0.005)
Firm fixed effects	No	Yes	Yes	Yes	Yes
No. Observations	10,009	10,009	10,009	10,009	9,896

Notes: Dependent variable if log(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.

TABLE 6 –
COEFFICIENT ESTIMATES FOR THE R&D EQUATION

	(1)	(2)	(3)	(4)	(5)
R&D treated as:	Exogenous	Exogenous	Exogenous	Exogenous	Endogenous
Distance Measure:	Jaffe	Jaffe	Jaffe	Mahalanobis	Jaffe
$Ln(SPILLTECH)_{t-1}$	0.092	0.117	-0.036	-0.176	0.205
	(0.017)	(0.074)	(0.040)	(0.101)	(0.093)
$Ln(SPILLSIC)_{t-1}$	0.371	0.078	0.033	0.224	0.014
	(0.013)	(0.035)	(0.019)	(0.048)	(0.047)
$Ln(R\&D/Sales)_{t-1}$			0.681		
			(0.015)		
Firm fixed effects	No	Yes	No	Yes	Yes
No. Observations	8,579	8,579	8,387	8,579	8,578

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.

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	0.242**	0.903**	0.579***	Yes
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	-0.072**	-0.136**	-0.087**	Yes
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Positive	0.423**	0.583***	0.302**	Yes
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	0.053	0.078	0.076	Yes
$\partial y_0/\partial r_\tau$	Productivity with SPILLTECH	Positive	0.103**	0.212**	0.078**	Yes
$\partial y_0/\partial r_m$	Productivity with SPILLSIC	Zero	0.010	0.015	-0.017	Yes
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Ambiguous	0.117	-0.176*	0.205**	-
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Ambiguous	0.078**	0.224**	0.014	-

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 –
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
$Ln(SPILLTECH)_{t-1}$	1.302	0.516	0.457	-0.263
	(0.613)	(0.287)	(0.222)	(0.239)
$Ln(SPILLSIC)_{t-1}$	-0.472	0.101	-0.046	0.307
	(0.159)	(0.824)	(0.116)	(0.112)
Observations	358	277	343	395

B. Pharmaceuticals

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cite-weighted patents	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	1.611	1.714	0.638	-0.683
	(0.674)	(0.860)	(0.279)	(0.418)
$Ln(SPILLSIC)_{t-1}$	-1.324	-0.046	-0.396	1.234
	(0.612)	(0.309)	(0.339)	(0.547)
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
$Ln(SPILLTECH)_{t-1}$	2.299	1.163	0.477	0.530
	(0.869)	(0.577)	(0.339)	(0.296)
$Ln(SPILLSIC)_{t-1}$	-0.118	-0.046	0.154	0.025
	(0.456)	(0.352)	(0.182)	(0.126)
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)) corresponds to column (2) of Table 4; real sales (column 3) corresponds to column (2) of Table 5; R&D/Sales (column (4)) corresponds to column (2) of Table 6.

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
Closeness Measures							
1. All	Jaffe	20.0	38.1	18.1	3,000	0.015	0.038
2. All	Mahalanobis	27.7	61.7	34	3,000	0.030	0.174
3. All	Jaffe, IV	15.5	26.6	11.1	3,000	0.015	0.038
Size splits							
4. Largest size quartile	Jaffe	20.4	46.3	25.9	29,700	0.015	0.054
5. Second size quartile	Jaffe	19.8	38.0	18.2	5,900	0.012	0.037
6. Third size quartile	Jaffe	20.0	35.2	15.2	1,680	0.016	0.033
7. Smallest size quartile	Jaffe	19.9	32.9	13	370	0.018	0.029
Industry splits							
8. Computer hardware	Jaffe	77.8	104.6	26.8	2,140	0.019	0.032
9. Pharmaceutical	Jaffe	107.1	108.7	1.6	2,250	0.027	0.047
10. Telecommunications Equipment	Jaffe	54.4	104.6	50.2	920	0.027	0.030

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 row recalculates this using the Jaffe closeness measure with the tax credit instruments for firm-level R&D (column (6) Table 7). The next four rows recalculate these figures for firms based on their position in the employment size quartiles. The last three rows calculate the spillovers for the three high-technology industries we estimated separately in Table 8. For these we used the coefficients from Table 8 and the sales/R&D stocks from the relevant industry.

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 – TREATING R&D AS ENDOGENOUS USING TAX PRICES AS INSTRUMENTAL VARIABLES

	(1)	(2)	(3)	(4)
Dependent variable:	Log(R&D)	Log(R&D)	Log(R&D)	Log(R&D)
Second stage specification:	Tobin's Q	Patents	Productivity	R&D
State Tax Credit component of R&R user cost$_t$	-1.665	-2.452	-0.396	-1.665
	(0.407)	(0.435)	(0.264)	(0.407)
Firm Tax Credit component of R&D user cost$_t$	-0.721	-1.080	-0.586	-0.721
	(0.108)	(0.146)	(0.077)	(0.108)
F-test of the two excluded instruments	29.59	44.88	29.80	29.59
No. Observations	9,271	6,012	8,806	9,271

Notes: These are the first stages corresponding to the final columns of Tables 3-6 which treat R&D as endogenous (i.e. Table 3 column (6), Table 4 column (5), Table 5 column (5) and Table 6 column (5). All other exogenous variables are included in these specifications. Standard errors (in brackets) are robust to arbitrary heteroskedacity and allow for first order serial correlation using the Newey-West procedure. All columns include year dummies and fixed effects.

TABLE A3 –
ALTERNATIVE CONSTRUCTION OF SPILLSIC USING BVD INFORMATION INSTEAD OF COMPUSTAT SEGMENT DATASET

	(1)	(2)	(3)	(4)
Dependent variable:	Tobin's Q	Cite weighed Patents	Ln(Real Sales)	Ln(R&D/Sales)
	Fixed Effects	Fixed Effects	Fixed effects	Fixed Effects + Dynamics
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)
Ln(R&D Stock) $_{t-1}$		0.249	0.057	
		(0.061)	(0.008)	
Ln(Capital) $_{t-1}$			0.169	
			(0.014)	
Ln(Labor) $_{t-1}$			0.625	
			(0.018)	
Ln(R&D Stock/Capital Stock)$_{t-1}$	0.902			
	(0.221)			
Pre-sample fixed effect		0.591		
		(0.051)		
No. Observations	7,269	6,696	7,364	6,445

Notes: This table summarizes the results from the "preferred specifications" using the alternative method of constructing SPILLSIC based on BVD data (see Appendix B). The market value equation in column (1) corresponds to the specification in Table 3 column (2); the patents equation in column (2) corresponds to the specification in Table 4 column (2); the productivity equation in column (3) corresponds to the specification in Table 5 column (2) and the R&D equation in column (4) corresponds to the specification in Table 6 column (2). All columns include year dummies and fixed effects.

TABLE A4 –
ALTERNATIVE CONSTRUCTION OF SPILLOVER VARIABLES

A. Baseline (Summarized from Tables 3-6 above)				
	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cites	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.242	0.423	0.103	0.117
	(0.105)	(0.071)	(0.046)	(0.074)
$Ln(SPILLSIC)_{t-1}$	-0.072	0.054	0.010	0.078
	(0.032)	(0.034)	(0.012)	(0.035)
Observations	9,944	9,023	10,009	8,579
B. Alternative Based on $SPILLSIC^A$ (and SPILLTECH unchanged)				
	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cites	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.241	0.423	0.109	0.098
	(0.104)	(0.071)	(0.046)	(0.075)
$Ln(SPILLSIC)_{t-1}$	-0.070	0.070	0.001	0.091
	(0.032)	(0.040)	(0.012)	(0.033)
Observations	9,958	9,046	10,023	8,579
C. Alternative Based on $SPILLSIC^A$ and $SPILLTECH^A$				
	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Cites	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.190	0.538	0.088	0.109
	(0.093)	(0.095)	(0.041)	(0.066)
$Ln(SPILLSIC)_{t-1}$	-0.071	0.057	0.001	0.085
	(0.033)	(0.041)	(0.012)	(0.033)
Observations	9,958	9,046	10,023	8,579
D. Alternative Based on $SPILLTECH^{TFK}$ (see Thompson and Fox-Kean, 2005)				
	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Patents	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	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

Notes: This table summarizes the results from the "preferred specifications" using the alternative methods of constructing the distance metrics (see text and Appendix C). The market value equation in column (1) corresponds to the specification in Table 3 column (2); the patents equation in column (2) corresponds to the specification in Table 4 column (2); the productivity equation in column (4) corresponds to the specification in Table 5 column (2) and the R&D equation in column (3) corresponds to the specification in Table 6 column (2). Panel A summarizes the results in Tables 3-6 using the standard methods where $SPILLSIC_i = \sum_{j,j\neq i} SIC_{ij} G_j$ with $SIC_{ij} = \frac{S_i S_j^{'}}{\sqrt{(S_j S_j^{/})}\sqrt{(S_i S_i^{/})}}$. By contrast in Panels B and C $SPILLSIC_i^A = \sum_{j,j\neq i} (S_i S_j^{'}) G_j$ (with $SPILLTECH^A$ defined analogously). Panel E uses a more disaggregated version of technology classes, $SPILLTECH^{TFK}$, as suggested by Thompson and Fox-Kean, 2005). See text for more details.