Identifying technology spillovers and product market rivalry*

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Abstract

Support for R&D subsidies relies on empirical evidence that R&D "spills over" between firms. But 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 between 1980 and 2001 we show that both technology and product market spillovers operate, but technology spillovers quantitatively dominate. The spillover effects are also present when we analyze three high tech sectors in finer detail. Using the model we evaluate the net spillovers from three alternative R&D subsidy policies.

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1. Introduction

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

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

This paper develops a methodology to identify the separate effects of technol-

[1] See, for example, Philippe Aghion and Peter Howitt (1992) or Michael Spence (1984). Zvi Griliches (1992) and Wolfgang Keller (2004) have surveys of the literature.

ogy and product market spillovers and implements this methodology on a large panel of U.S. companies. Our approach is based on two 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, 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 positions in *technology* space and *product market* space using information on the distribution of its patenting (across technological 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 allow us to distinguish empirically between technology and product market spillovers.[3]Applying this approach to a panel of U.S. firms for a twenty year period (1981-2001) we find that both technological and product market spillovers are present and quantitatively important. Nevertheless, the technology spillover effects are larger in magnitude than the rivalry effects so there will still be under-investment in R&D from a social perspective. We also find (weaker) evidence that R&D by product market rivals is, on average, a strategic complement for a firm's own R&D. Using parameter estimates from the model we evaluate the impact of three different R&D subsidy policies and show that the typical focus of R&D support for small and medium firms may be misplaced, if

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

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

the objective is to redress market failures associated with technology spillovers.

Our paper has its antecedents in the empirical literature on knowledge spillovers. The dominant approach has been to construct a measure of outside R&D (the "spillover pool") and include this as an extra term in addition to the firm's own R&D in a production, cost or innovation function. The simplest version is to measure the spillover pool as the stock of knowledge generated by other firms in the industry (e.g. Jeremy Bernstein and M. Ishak 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 $SPILLTECH_i = \Sigma_{j,j\neq i} w_{ij} G_j$ 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 Adam 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

[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. Daron Acemoglu, Philippe Aghion, Claire Lelarge, John Van Reenen and Fabrizzio Zilibotti, 2006).

in product market space[5].

Two caveats are in order about the scope of this paper. First, we focus on technology and product market spillovers, rather than "rent spillovers" that arise from mismeasured input prices[6]. Second, even in the absence of rent spillovers and strategic effects, it is not easy to distinguish a spillovers interpretation from the possibility that positive interactions are "just a reflection of spatially correlated technological opportunities" (Zvi Griliches, 1998). 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 "reflection problem" discussed by Charles Manski (1991). A necessary condition for identification is prior information that specifies the relevant reference group and this is the role played by a knowledge weighting matrix. Beyond that, we place parametric structure on the nature of interactions through our firm specific pairings in technology space and product market space to achieve identification. In addition, we attempt to mitigate the reflection problem by exploiting the panel structure of our data using various controls for the unobserved shocks (such as firm specific effects and measures of industry demand).

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 econometric findings are presented in Section 5. In Section 6 we use the

[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. Also note that the extent of knowledge spillovers may be infuenced by geographic proximity (the classic paper is Adam Jaffe, Manuel Trajtenberg and Rebecca Henderson, 1993), research collaborations (Jasjit Singh, 2005), and other factors.

[6]As Zvi Griliches (1979) pointed out, rent spillovers occur when R&D-intensive inputs are purchased from other firms at less than their full 'quality-adjusted' price. Such spillovers are simply consequences of conventional measurement problems and essentially mis-attribute the productivity gains to firms that purchase the quality-improved inputs rather than to the firms that produce them.

preferred estimates to evaluate the social returns generated by three R&D subsidy policies. The concluding remarks summarize the key results and directions for future research.

2. Analytical Framework

We consider the empirical implications of a non-tournament model of R&D with technology spillovers and strategic interaction in the product market[7]. We study a two-stage game. In stage 1 firms decide their R&D spending and this produces knowledge (which we will empirically proxy by patents and TFP) that is taken as pre-determined in the second stage. 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.

[7] This approach has some similarities to Chad Jones and John Williams (1998) who examine an endogeneos 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.

Firstly, we allow other 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-tournamamament model which is the focus of this section). Thirdly, we allow patenting to be endogenously chosen by firms rather than only an indicator of knowledge, k. The comparative static results are shown to be robust to all these extensions with one exception that we will discuss below.

Stage 2

Firm $0's$ profit function is $\pi(x_0, x_m, k_0)$. We assume that the function π is common to all firms. Innovation output k_0 may have a direct effect on profits, as well as an indirect (strategic) effect working through x. For example, if k_0 increases the demand for firm 0 (e.g. product innovation), its profits would increase for any given level of price or output in the second stage.[8]

The best response for firms 0 and m are given by $x_0^* = \arg\max\ \pi(x_0, x_m, k_0)$ and $x_m^* = \arg\max\ \pi(x_m, x_0, k_m)$, 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, decreasing in k_m and concave[9].

Stage 1

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

[8] We assume that innovation by firm m affects firm $0's$ profits only through x_m, which is plausible in most contexts. This can be extended without changing the predictions of the model.

[9] The assumption that $\Pi(k_0, k_m)$ declines 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.

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. By comparative statics,

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

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.

Comparative statics also yield

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

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

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

Table 1 summarizes the basic predictions. The intuition for these results is straightforward. In the case where there is are no product market rivalry or technology spillovers, R&D by other firms should have no influence on firm 0's decisions or market value. Now suppose there are technology spillovers. 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. 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.*

[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., Glenn Loury, 1979; Thomas Lee and Lewis Wilde, 1980) and more recent models of sequential races (Philippe Aghion, Christopher Harris and John Vickers, 1997). There are patent race models where this is not the case, but they involve a "discouragement effect" whereby a follower may give up if the R&D gap gets so wide that it does not pay to invest to catch up (Christopher Harris and John Vickers, 1987).

We turn next to the effects of R&D by firms that are close in product market space. First, product market rivals' R&D has a direct, negative influence on firm 0's value, through the business stealing effect. This can work by reducing the firm's profit margins or market shares, or both. Second, R&D by product market rivals has no effect on the firm's production of knowledge and thus no direct effect on the number of patents, which is our main empirical proxy for firm knowledge. For the same reason, product market rivals' R&D does not affect the level of (physical) total factor productivity. 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}. 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. 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). It turns out there is some empirical evidence in our data for this effect[11]. We also note that if the measure of total factor productivity is contaminated by imperfect price deflators, product market rival R&D could be negatively correlated with R&D because it will depress firm 0's

[11] 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 Bronwyn Hall and Rosemarie Ziedonis (2001), and Michael Noel and Mark Schankerman (2006).

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

3. 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. 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[12]. Since our method requires information on patenting, we kept all firm years with a positive patent stock (so 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. Appendix B provides details on all datasets.

[12] See Bronwyn Hall, Adam Jaffe and Manuel Trajtenberg (2005) and Adam Jaffe and Manuel Trajtenberg (2002). We also constructed a forward cite-weighted patent count as a quality adjusted measure. This produced very similar results to the simpler raw count except in specific industries, such as pharmaceuticals (see Table 11).

3.1. 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 Adam 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 $TECH_{ij} = TECH_{ji}$.[13] 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 by firm j in year t. The R&D stock is calculated using a perpetual inventory method, $G_t = R_t + (1-\delta)G_{t-1}$, with a depreciation rate (δ) of 15% (Hall et al, 2005).

3.2. 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

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

of business). On average each firm report 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.[14] 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:

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

There are several issues with calculating the key $SPILLSIC$ and $SPILLTECH$ measures, which we discuss in Sections 3.3 and 3.4, paying particular attention to alternative datasets to the Compustat Segment Data and alternative functional forms of the measures of distance.

3.3. Alternative to Compustat Segment Data: the BVD Dataset

The breakdown of firm sales into four digit industries in the Compustat Segment Dataset may be biased. Belen Villalonga (2004) carefully investigated the diversification discount that typically obtained when using Compustat Segment Dataset.

[14] 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).

She found that using a US Census Bureau database called BITS (Business Information Tracking Service) the diversification discount turns into a premium. Villalonga argued that this is because firms "strategically" report segment data breakdowns in their company accounts. Unfortunately BITS is only available for use at the US Census Bureau, making it difficult to access publicly. We therefore turned to an alternative datasource called the BVD (Bureau Van Dijk) Database. This contains cross-sectional industry and ownership information on around ten million subsidiaries 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. Since we are interested in global activity (to match Compustat's global accounting coverage) the BVD database seems a good alternative to BITS (BITS refers only to activities within the United States and many of our firms are multinationals).

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[15] across four digit industries (essentially summing across all the global subsidiaries). On average we matched 29.6 subsidiaries per firm: 11.4 of these are in the US and Canada and 18.2 of these are in Europe. We are able to match three-quarters of all firms in our Compustat sample to the BVD dataset which represents 84% of all employment and 95% of all R&D. Since the BVD-Computsat match has fewer firms, our baseline results use the Computsat Segment Dataset and we use the BVD-based measures to check robustness.

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

[15] We assume that sales is proportional to employment. Like BITS many subsidiaries do not report sales in the BVD Dataset.

firms is 0.592. The within-firm over-time variation identifies our empirical results as we control for fixed effects, so it is reassuring that the within-firm correlation of $\ln(SPILLSIC)$ across the Compustat Segment and BVD datasets rises to 0.737.

3.4. Alternative distance metrics

We have chosen particular functional forms of our distance metric based on Jaffe (1986), but there are obviously a host of alternatives. To see the issues consider a general form of the relationship between an outcome measure Q_i (e.g. the market value of firm i) and the product market spillovers from other firms in the economy where we abstract from all other factors (similar issues arise for $SPILLTECH$ so for notational simplicity we focus on just $SPILLSIC$):

$$Q_i = g(S_i, \mathbf{S}_j, R_j; \boldsymbol{\theta}) \tag{3.5}$$

S_i is a vector of firm i's sales distribution across industries (as above), $\mathbf{S}_j$ is the matrix of all other firms' sales distribution vectors, R_j is the vector R&D for each firm j, $\boldsymbol{\theta}$ is a parameter vector and $g(.)$ is an unknown function mapping sales distributions and R&D to firm i's outcome. Different assumptions over the functional form of $g(.)$ will define the spillover relationship. The only substantive assumption we have made in equation (3.5) is that firm sales are the relevant measure for where companies are located in product market space. Empirically, we have to place more structure over equation (3.5) to operationalize it in our application. Joris Pinske, Margaret Slade and Craig Brett (2002) discuss general issues in constructing semi-parametric versions of equation (3.5). Our approach in this paper is to consider several possible parametric versions of equation (3.5).

Our canonical case is based on Jaffe (1986) as this has proven a fruitful approach in the technology spillover literature and it seems natural to keep this as a benchmark for $SPILLTECH$ and to take a symmetrical approach when considering product market spillovers, $SPILLSIC$. One unattractive feature of this definition of 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[16] and can also be rationalized by a simple model of independent markets coupled with aggregation (see Appendix C.1). In this case the alternative product market spillover measure is $SPILLSIC^A_{it} = \Sigma_{j,j\neq i} SIC^A_{ij} G_{jt}$ and the analogous measures for technology $TECH^A_{i,j} = T_i T'_j$ and $SPILLTECH^A_{it} = \Sigma_{j,j\neq i} TECH^A_{ij} G_{jt}$. However, this alternative, $SIC^A_{i,j}$, has an important disadvantages as compared to the Jaffe measure, $SIC_{i,j}$. In particular, it is sensitive to arbitrary industry boundaries that affect overlap in sales distributions. To illustrate, consider the following case with two equally sized firms and two sectors. In scenario (i) both firms are in the same sector and in scenario (ii) each firm is split 50-50 in the two sectors. $SIC_{i,j}$ will be the same in both cases ($SIC_{i,j} = 1$) whereas $SIC^A_{i,j} = 1$ in scenario (i) and $SIC^A_{i,j} = 0.5$ in scenario (ii).

We also consider a third alternative based on Glenn Ellison and Edward Glaeser's (1997) theory-based measure of "co-agglomeration" (see Appendix C.2 for exact definition of $SPILLTECH^{EG}_{it}$). In the Ellison-Glaeser model, plants choose optimally where to set-up and will tend to locate close to other plants if they can benefit from spillovers. In our context, firms will choose to locate in particular technological classes if they believe they can benefit from spillovers from other firms operating in the same technology classes. Obviously this argument

[16] To see this consider an economy with three possible sectors A, B and C. Firm 1 sells 10 units in industry A and B (and performs 10 units of R&D in these industries). Firm 2 sells 10 units in industry B and C (and performs 10 units of R&D in these industries). Firm 3 sells 10 units only in industry B (and performs 10 units of R&D in this industry). It is not obvious why the optimizing behavior of firm 1 should be different if she faces just firm 2 or just firm 3. But our basic Jaffe method generates $SPILLSIC_{12} = 10$ (=0.5*20) and $SPILLSIC_{13} =$ 7.07(=0.707*10). By contrast, $SPILLSIC^A_{12} = SPILLSIC^A_{13} = 5$

does not apply to $SPILLSIC$ as firms will want to avoid rivals who are "close" to them in product market space.

Finally, Peter Thompson and Marianne Fox-Kean (2005) have suggested that the three digit patent class may be too coarse and a finer disaggregation is better for measuring spillovers. We therefore constructed $SPILLTECH_{it}^{TFK}$ which uses four digit patent classes to calculate the distance measure, $TECH_{it}^{TFK}$. As pointed out by Rebecca Henderson, Adam Jaffe and Manuel Trajtenberg (2005) finer disaggregation of patents classes is not necessarily superior as the classification is subject to a greater degree of measurement error[17].

Ultimately there is no one obvious, objectively superior distance metric for spillovers. We take a pragmatic approach and compare our results across all four alternative measures in order to check whether robust results are obtained.

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

In order to distinguish between the effects of technology spillovers and product market interactions we need variation in the distance metrics in technology and product market space. To gauge this we do three things. First, we calculate the raw correlation between the measures SIC and $TECH$, which is 0.469, positive but well below unity, implying independent variation in the two measures. 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 logs 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 at significant at the one per cent level). Second, we plot SIC against TEC in Figure 1 from which it is apparent that the positive correlation we observe is caused by a

[17] This is because 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.

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 spaces, and close in product market but distant in technology space.

Table 2 provides some basic descriptive statistics for the accounting and patenting data, and the technology and product market closeness measures, $TECH$ and SIC. The sample firms are large (mean employment is over 18,000), but with much heterogeneity in size, R&D intensity, patenting activity and market valuation. The two closeness measures also differ widely across firms.

[Table 2 about here]

4. Econometrics

4.1. Generic Issues

There are four main equations of interest that we wish to estimate: a market value equation, a patents equation, a productivity equation and a R&D equation.[18]. There are generic econometric issues with all three equations which we discuss first before turning to specific problems with each equation. We are interested in investigating the relationship

$$y_{it} = x_{it}'\beta + u_{it} \tag{4.1}$$

where the outcome variable for firm i at time t is y_{it}, the variables of interest (especially $SPILLTECH$ and $SPILLSIC$) are x_{it} and the error term, whose properties we will discuss in detail, is u_{it}.

First, we have the problem of unobserved heterogeneity. We will present estimates with and without controlling for correlated fixed effects (through including

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

a full set of firm specific dummy variables). The time dimension of the company panel is relatively long, so the "within groups bias" on weakly endogenous variables (see Nickell, 1981) is likely to be small, subject to the caveats we discuss below[19]. Second, we have the issue of the endogeneity due to transitory shocks. To mitigate these we condition on a full set of time dummies and a distributed lag of industry sales[20]. Furthermore we lag all the other variables on the right hand side of equation (4.1) by one period to overcome any immediate feedback effects[21]. Third, equation (4.1) is static, so we experiment with more dynamic forms. In particular we present specifications including a lagged dependent variable. Finally, there are inherent non-linearities in the models we are estimating (such as the patent equation) which we discuss next.

4.2. Market Value equation

We adopt a simple linearization of the value function proposed by Zvi Griliches (1981)[22]

$$\ln\left(\frac{V}{A}\right)_{it} = \ln\kappa_{it} + \ln\left(1+\gamma^{v}\left(\frac{G}{A}\right)_{it}\right) \tag{4.2}$$

where V is the market value of the firm, A is the stock of tangible assets, G is the R&D stock, and the superscript v indicates that the parameter is from the market value equation. The deviation of V/A (also known as "Tobin's average Q") from

[19] We have between four and twenty-one years of continuous firm observations in our sample. In the R&D equation, for example, the mean number of observations per firm is eighteen.

[20] The industry sales variable 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.

[21] This is a conservative approach as it is likely to reduce the impact of the variables we are interested in. An alternative (in the absence of obvious external instruments) is to explicitly use the lags as instruments - we report some experiments using these GMM based approaches in the results section.

[22] See also Jaffe (1986), Bronwyn Hall et al (2005) or Jenny Lanjouw and Mark Schankerman (2004).

unity depends on the ratio of the R&D stock to the tangible capital stock (G/A) and lnκ_{it}. We parameterize this as

$$\ln \kappa_{it} = \beta_1^v \ln SPILLTECH_{it} + \beta_2^v \ln SPILLSIC_{it} + Z_{it}^{v\prime}\beta_3^v + \eta_i^v + \tau_t^v + \upsilon_{it}^v$$

where η_i^v is the firm fixed effect, τ_t^v is a full set of time dummies, Z_{it}^v denotes other control variables such as industry demand, and υ_{it}^v is an idiosyncratic error term. If $\gamma^v(G/A)$ was "small" then we could approximate $\ln\left(1+\gamma^v\left(\frac{G}{A}\right)_{it}\right)$ by $\gamma^v\left(\frac{G}{A}\right)_{it}$. But this will not be a good approximation for many high tech firms and, in this case, equation (4.2) should be estimated directly by non-linear least squares (NLLS). Alternatively one can approximate $\ln\left(1+\gamma^v\left(\frac{G}{A}\right)_{it}\right)$ by a series expansion with higher order terms (denote this by $\phi(\frac{G}{A})$), which is more computationally convenient when including fixed effects. Empirically, we found that a sixth order series expansion was satisfactory. Taking into consideration the generic econometric issues over endogeneity discussed above, our basic empirical market value equation is:

$$\begin{aligned}\ln\left(\frac{V}{A}\right)_{it} &= \phi((G/A)_{it-1}) + \beta_1^v \ln SPILLTECH_{it-1} + \beta_2^v \ln SPILLSIC_{it-1} \\ &\quad + Z_{it}^{v\prime}\beta_3^v + \eta_i^v + \tau_t^v + \upsilon_{it}^v \qquad (4.3)\end{aligned}$$

4.3. Patent Equation

We use a version of the Negative Binomial model to analyze our patent count data. Models for count data assume a first moment of the form:

$$E(P_{it}|X_{it}, P_{it-1}) = \exp(x_{it}'\beta^p)$$

where $E(.|.)$ is the conditional expectations operator and P_{it} is a (possibly cite weighted) count of the number of patents. In our analysis we want to allow both for dynamics and fixed effects, and to do so we use a Multiplicative Feedback

Model (MFM). The conditional expectation of the estimator is:

$$\begin{aligned} E(P_{it}|X_{it}, P_{it-1}) &= \exp\{\delta_1 D_{it} \ln P_{it-1} + \delta_2 D_{it} + \beta_1^p \ln SPILLTECH_{it-1} + \\ &\quad \beta_2^p \ln SPILLSIC_{it-1} + Z_{it}^{p\prime}\beta_3^p + \eta_i^p + \tau_t^p\} \end{aligned} \tag{4.4}$$

where D_{it} is a dummy variable which is unity when $P_{it-1} > 0$ and zero otherwise.

The variance of the Negative Binomial under our specification is:

$$V(P_{it}) = \exp(x_{it}'\beta^p) + \alpha \exp(2x_{it}'\beta^p)$$

where the parameter, α, is a measure of "over-dispersion", relaxing the Poisson restriction that the mean equals the variance ($\alpha = 0$).

We introduce firm fixed effects into the count data model using the "pre-sample mean scaling" method of Richard Blundell, Rachel Griffith and John Van Reenen (1999). This relaxes the strict exogeneity assumption underlying the conditional maximum likelihood approach of Jerry Hausman, Bronwyn Hall and Zvi Griliches (1984). Essentially, we exploit the fact that we have a long pre-sample history (from 1970 to at least 1980) of patenting behaviour 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 Richard Blundell, Rachel Griffith and Frank Windmeijer, 2002).

4.4. Productivity Equation

Although we consider more complex forms, the basic production function is of the R&D augmented Cobb-Douglas form:

$$\ln Y_{it} = \beta_1^y \ln SPILLTECH_{it-1} + \beta_2^y \ln SPILLSIC_{it-1} + Z_{it}^{y\prime}\beta_3^y + \eta_i^y + \tau_t^y + \upsilon_{it}^y \quad (4.5)$$

The key variables in $Z_{it}^{y\prime}$ are the other inputs into the production function - labour, capital, and the own R&D stock. If we measured output correctly then the predictions of the marginal effects of $SPILLTECH$ and $SPILLSIC$ in equation (4.5) would be the qualitatively same as that in the patent equation, Technology spillovers improve total factor productivity (TFP), whereas R&D in the product market should have no impact on TFP (conditional on own R&D and other inputs). In practice, however, we measure output as "real sales" - firm sales divided by an industry price index. Because we do not have information on firm-specific prices, this induces measurement error. 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 (4.5) are the same as those of the market value equation. Controlling for industry sales dynamics (see Tor Klette and Zvi Griliches, 1996) and fixed effects should go a long way towards dealing with the problem of firm-specific prices. In the results section, we show that that the negative coefficient on $SPILLSIC$ essentially disappears when we control for these additional factors.

4.5. R&D equation

We write the R&D intensity equation as:

$$\ln(R/Y)_{it} = \alpha^r \ln(R/Y)_{it-1} + \beta_1^r \ln SPILLTECH_{it-1} + \beta_2^r \ln SPILLSIC_{it-1} + Z_{it}^{r\prime}\beta_3^r + \eta_i^r + \tau_t^r + \upsilon_{it}^r \quad (4.6)$$

where Y is real sales. The main issue to note is that the contemporaneous value of $SPILLTECH$ and $SPILLSIC$ would be particularly difficult to interpret in equation (4.6) due to the reflection problem (Manski, 1991). A positive correlation could either reflect strategic complementarity or common unobserved shocks that are not controlled for by the other variables in equation (4.6). We address identification explicitly in the next sub-section explicitly.

4.6. Identification Issues

Since we are attempting to identify a "social effect" we must address the Manski (1991) identification issues. The paper has no magic bullet, but does have several advantages over other contributions in the spillover literature. We do not attempt to non-parametrically identify the spillover effects (which Manski shows is not possible) and instead make some parametric assumptions over the form of distance metric. Fundamentally, identification of the various spillover effects for firm i comes from two elements - a time invariant "distance" between firm i and all other firms and the time-varying R&D of other firms. For example, the fact that we measure two firms as close in technology space indicates that they *may* be benefiting from mutual inter-firm spillovers. But this is not necessarily the case, the firms will also appear close in technology space if they have some comparative advantage in utilizing similar technologies but there is no actual technology spillover between them[23]. Instead, our application utilizes the fact that there are exogenous shocks differentially affecting the R&D of other firms in the economy. These shocks can arise for a variety of reasons such as the US R&D tax credit that created very heterogeneous incentives across different companies [24]. Another

[23] For the same reason, Ellison and Glaeser's (1997) agglomeration parameter cannot identify between regional concentration of an industry arising from genuine spillovers and that arising from natural advantage (e.g. the presence of a coastline).

[24] Brownyn Hall (1992) shows that there is much heterogeneity in the tax-adjusted user cost of R&D across US firms because of the design of the credit (rolling "base", tax exhaustion, etc.). She uses this firm and time specific variation to identify substantial effects of the tax credit on the R&D behaviour of US firms in her sample of Compustat firms.

example would be the end of the Cold War which led to large falls in the degree of government support for defence-related R&D.

We identify spillovers from the assumption that a given increase in the R&D of firm j should have a larger effect on firm i if it is "close" and a smaller effect on firm i if it is "distant". Thus, we can control for distance in a non-parametric way (through firm fixed effects) and for general changes in R&D (time dummies) and seek to identify from the interaction. Of course, this does not remove all identification issues. For example, consider the problem of a transitory unobserved shock specific to a pair of firms close in technology space - this could simultaneously raise their R&D, patents, productivity and market value. Our approach tries to mitigate this problem in several ways. First, we include many controls for this possible shock - time dummies, industry sales, firm fixed effects and time varying other firm-level covariates in some regressions (e.g. sales, capital, labor, own R&D, etc.). Second, we also lag all the firm level variables to avoid contemporaneous feedback). Most importantly, the model predicts differential responses across different spillover variables in different equations. Consider the market value equation, for example. We predict that R&D by firms close in the product market ($SPILLSIC$) should have a *negative* effect on market value whereas R&D by firms whereas firms close in technology space ($SPILLTECH$) should have a *positive* effect on market value. So any shock that is raising other firms' R&D generally is predicted to have a differential effect on a firm depending on its closeness in the product space vs. technology space. Furthermore, in the R&D equation $SPILLSIC$ is predicted to have a positive effect on R&D if there is strategic complementarity (which is what we find). It is hard to come up with a story for why an omitted shock should increase firms' R&D but depress firms' market value. So although we can never rule out the possibility that some complex interaction of omitted shocks drives our results in a world without spillovers, it seems unlikely.

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. We present specifications with and without fixed effects. The coefficients of the other variables in column (1) were close to those obtained from nonlinear least squares estimation[25]. 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. These are both contrary to the predictions of the theory. Finally, we find that the *growth* of industry sales affects the firm's market value (the coefficients are fairly close to each other but of opposite signs), which probably reflects unobserved demand factors.

When we allow for fixed effects, the estimated coefficient on $SPILLTECH$ switches signs and becomes positive and significant as compared to column (1)[26]. A ten percent increase in $SPILLTECH$ is associated with a 2.4 percent increase in market value. At sample means, this implies that an extra dollar of $SPILLTECH$ is associated with an increase in the recipient firm's market value of 4.3 cents. That is if another firm with perfect overlap in technology areas ($TECH = 1$) raised its R&D by one dollar, we predict that the firm's market value would rise by 4.3 cents. Recall that we include a sixth-order series of the

[25] 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).

[26] 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).

ratio of own-R&D stock to tangible capital, G/A, in order to capture the nonlinearity in the value equation. Using the parameter estimates on these G/A terms, we obtain an elasticity of market value with respect to own R&D of 0.242 (at the mean). Evaluated at the sample means, this implies that an extra dollar of R&D stock is associated with \$1.19 higher market value. This estimate is higher than the 86 cent figure obtained by Hall et al (2005) over an earlier sample period. Comparing these estimates we conclude that the private value of a dollar of technology spillover is only worth (in terms of market value) about 3.6 percent as much as a dollar of own R&D.

With fixed effects, the estimated coefficient on $SPILLSIC$ is now negative and significant at the five percent level. Evaluated at the sample means, a ten percent increase in $SPILLSIC$ is associated with a 0.72 percent reduction in market value. This implies that an extra dollar of $SPILLSIC$ is associated with a reduction of a firm's market value by 4.6 cents. Interestingly, the negative effect of an extra dollar of product market rivals' R&D is similar in magnitude to the positive effect of a dollar of technology (R&D) spillovers. Of course, the net effect of R&D spending by other firms will depend on the product market and technological distance between those firms ($TECH$ and SIC). Using our parameter estimates, we can compute the effect of an exogenous change in R&D for any specific set of firms (see Section 6).

In short, once we allow for unobserved heterogeneity in the specification of the market value equation, the signs of the two spillover coefficients are consistent with the prediction from the theory outlined in Section 2. 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 prices.

It is also worth noting that, if we do not control for the product market rivalry effect, the estimates of both spillover variables are biased toward zero. Column (3) presents the estimates when $SPILLSIC$ is omitted. The coefficient on $SPILLTECH$ declines and becomes statistically insignificant at the 5 per cent level. Failing to control for product market rivalry could lead us to miss the impact of technology spillovers on market value. 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.

Attenuation bias is exacerbated by fixed effects, but classical measurement error should bias the coefficients towards zero. This suggests that the change in the coefficients on the spillover variables between columns (1) and (2) when we introduce fixed effects is not due to classical measurement error as the coefficients become larger in absolute magnitude. Instead, it is likely that unobserved heterogeneity obscures the true impact of the spillover variables on market value. This could arise if we have not controlled sufficiently for firms who are closely clustered in high tech sectors - they will tend to have high value of $SPILLSIC$ and high Tobin's Q (since R&D will not perfectly control for intangible knowledge stocks). This will drive a positive correlation between the $SPILLSIC$ term and market value even in the absence of any technological or product market interactions. Fixed effects control for this unobserved heterogeneity[27].

[27] 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*).

5.2. Patents Equation

We turn next to the patents equation (Table 4). Column (1) presents the estimates in a static model with no controls for correlated individual effects. Unsurprisingly, larger firms and those with larger R&D stocks are much more likely to have more patents. $SPILLTECH$ has a positive and highly significant association with patenting, indicating the presence of technology spillovers. By contrast, the product market rivalry term has a much smaller coefficient and is not significant at the 5% level. The overdispersion parameter is highly significant here, rejecting the Poisson model in favour of the Negative Binomial.

In column (2) we control for firm fixed effects using the Blundell et al (1999) method of conditioning on the pre-sample patent stock (these controls are highly significant). Compared to column (1), the coefficient on the R&D stock falls but remains highly significant. A ten percent increase in the stock of own R&D generates a 2.8 percent increase in patents. The estimated elasticity of 0.28 points to more sharply diminishing returns than most previous estimates in the literature, but the earlier studies do not typically control for technology spillovers or the level of sales to capture demand factors. Turning to our key variables, allowing for fixed effects reduces the coefficient on $SPILLTECH$, but it remains positive and significant at the five per cent level.

Finally, in column (3) of Table 3 we present our preferred specification, which includes both firm fixed effects and lagged patent counts[28]. Not surprisingly, we find strong persistence in patenting (the coefficient on lagged patents is highly significant). In this model $SPILLTECH$ retains a large and significant coeffi-

[28] 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 1963). 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.

cient. Interestingly $SPILLSIC$ is positive and significant in this column whereas it was insignificant in the other columns. This is inconsistent with the simple model of Section 2, but is consistent with the extended model where patents are endogenously chosen (Appendix A.3)[29].

5.3. Productivity Equation

Table 5 contains the results from 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 is consistent with the simple theory that the marginal effects of spillovers on TFP should be zero. The negative sign on $SPILLSIC$ in column (1) could be due to rival R&D having a negative effect on prices 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, then 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 and becomes insignificant. The third column drops the insignificant $SPILLSIC$ term and is our preferred specification. These results are all consistent with the basic theory: R&D by firms close in technology space has a positive effect on knowledge (as proxied by TFP), but R&D by product market rivals has no effect.

[29] These results do not depend on the variance moment assumption underlying the Negative Binomial model, as using a GMM estimator that relies only on the first moment condition leads to qualitatively similar results

One might be concerned that there are heterogeneous technologies across industries, so we investigated allowing all inputs (labor, capital and R&D) to have different coefficients in each two-digit industry. Even in this demanding specification $SPILLTECH$ remained positive and significant at conventional levels[30]. We also experimented with using an estimate of real value added instead of real sales as the dependent variable which led to a similar pattern of results[31].

5.4. R&D Equation

We now turn to the coefficient estimates for the R&D intensity equation (Table 6). In the static specification without firm fixed effects (column (1)), we find that both technology and product market spillovers are present[32]. The positive coefficient on $SPILLSIC$ indicates that own and product market rivals' R&D are strategic complements. We control for the level of industry sales, which picks up common demand shocks and is positively associated with company R&D spending. When we include firm fixed effects (column (2)), the coefficient on $SPILLSIC$ declines substantially (to a quarter of its earlier value) but remains positive and significant. $SPILLTECH$ by contrast is no longer significant. In column (3) we do not include fixed effects but allow for dynamics (lagged R&D/sales). $SPILLSIC$ is significant at the five per cent level but the coefficient on $SPILLTECH$ is small and insignificant. In the final column we allow for both fixed effects and

[30] $SPILLTECH$ 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*).

[31] We followed the same method as Timothy Bresnahan et al (2002) in constructing value added (see Appendix B). When 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*).

[32] The spillover terms are significantly different in the fixed effects specifications compared to the OLS specifications (with industry dummies) at the five per cent level.

dynamics. In this column $SPILLSIC$ is still significant at the ten per cent level and the implied, long run effect are similar to the static specifications (0.103).[33]

To summarize, we find some evidence that R&D spending by a firm and its *product market rivals* are strategic complements, even after we controlling for industry level demand and firm fixed effects[34].

[Tables 7, 8 about here]

5.5. Implications of the Results

To summarize our main findings concisely, Table 7 compares the predictions from the model with the empirical results from Tables 3-6. The match between the theoretical predictions and the empirical results is quite close. The only exception is the positive effects of $SPILLSIC$ in the patents equation, but this is consistent with the extension of the model to allow for endogenous patenting. It gives some reason for optimism that this kind of approach, based on using multiple performance measures, can help disentangle the role of technology spillovers and product market rivalry.

The qualitative implications of our simple theory appear to be supported by the data. But what are their quantitative implications? We solve the system

[33] 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 Richard Blundell and Stephen 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 (4) 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.

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

of equations in the model (see Appendix E) to calculate the long-run equilibrium response of R&D, patents, productivity and market value to an exogenous stimulus to R&D.

We begin with a unit stimulus to the R&D spending of all firms, which we call "autarky". This stimulus is then "amplified" by the strategic complementarity in the R&D equation and the feedback through the production function. The magnitude of this amplification depends on how closely linked the firm is to its product market competitors, i.e. on the size of its average SIC. This long run response of R&D, for each firm, then contributes to the value of $SPILLTECH$ and $SPILLSIC$, which further amplifies the impact of the stimulus.

Table 8 summarizes the direct (autarky) effect and the amplification effects of a one percent R&D stimulus to all firms on each of the endogenous variables. As row 1 shows, strategic complementarity amplifies the original stimulus by 24.2%, so that the 1% stimulus generates 1.242% more R&D. The relative amplification effects on patents and productivity are larger because of the large $SPILLTECH$ effects. The relative amplification effect on market value is smaller because $SPILLSIC$ has a strong negative effect on market value which offsets much of the positive $SPILLTECH$ effect.

To a first approximation, this finding for productivity suggests that the social returns to R&D are about 3.5 times larger than the private returns (column (3) divided by column (1)). Thus when we allow for both technology spillovers and product market rivalry effects of R&D, we find that the former strongly dominate the latter. Furthermore, the positive amplification effect for market value suggests that the private sector will under-invest in R&D. This confirms the conventional wisdom of a role for policy support for R&D.

5.6. Alternative Construction of the Spillover Variables

5.6.1. Re-estimating all equations using $SPILLSIC$ constructed from the BVD Dataset

As discussed in the data section we were concerned that the Compustat Segment file may be inaccurate so we also considered calculating $SPILLSIC$ using the BVD Dataset. We summarize the results for the each of the four dependent variables (Tobin's Q, patents, productivity and R&D) for the most general econometric specifications with fixed effects and dynamics in Table 9 (full results are available from authors).

Although the sample size is slightly smaller, qualitatively the results are remarkably similar to the earlier tables. In the market value equation of column (1) $SPILLTECH$ is positive and significant at the five per cent level and $SPILLSIC$ is negative and significant at the five per cent level. In column (2), the patents equation, $SPILLTECH$ and $SPILLSIC$ are positive and significant at the five per cent level. In column (3), the productivity equation, $SPILLTECH$ is positive and significant at the five per cent level and $SPILLSIC$ is insignificant. In column (4), the R&D regression, $SPILLSIC$ is positive and significant at the five per cent level and $SPILLTECH$ is insignificant. These results are consistent with the strategic complementarity version of our model where both technology spillovers and product market rivalry are important.

[Tables 9 and 10 about here]

5.6.2. Alternative Distance Metrics

Table 10 presents some experiments with alternative distance metrics discussed in Sub-section 3.4. Panel A summarizes the results from Tables 3 through 6 as a baseline. Panel B presents the results using $SPILLSIC^A$, but keeps $SPILLTECH$

as in the baseline case. Panel C uses both $SPILLSIC^A$ and $SPILLTECH^A$ and Panel D considers using our version of the Ellison-Glaeser co-agglomeration measure, $SPILLTECH^{EG}$. Panel E uses the four digit patent classes instead of three digit patent classes, $SPILLTECH^{TFK}$.

The results appear very robust. Looking over Panels B through E of Table 10 the coefficient on $SPILLTECH$ is positive in all twelve specifications of the value equation, patent equation and production function (and is significant at the ten per cent level or more in ten cases out of the twelve regressions). The coefficient on $SPILLSIC$ is always negative and significant at the ten per cent level or more in the value equation and insignificant in the productivity equations. $SPILLSIC$ is positive in all of the R&D and patent equations, and is significant at the ten per cent level or greater in Panels B, C and D. The only difference is for $SPILLTECH$ in the R&D regressions in Panel D where it is significant and negative (like the baseline it is insignificant in the other panels). Since the sign of $SPILLTECH$ is theoretically ambiguous, this is not much of a problem.

Taking Tables 9 and 10 together, we conclude that the main findings are robust across using a large number of alternative constructions of the distance metric using different datasets and different functional firms. The weakest result is the finding of strategic complementarity. Overall, though, these results give us more confidence in our simple model.

5.7. Econometric results for three high-tech industries

We have used both cross firm and cross-industry variation (over time) to identify the technology spillover and product market rivalry effects. An obvious criticism is that pooling across industries disguises heterogeneity and 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 reasonable number of firms to estimate our key equations - Computer hardware, Pharmaceuticals, and Telecommunications Equipment. The results from these experiments are summarized in Table 11.

The results from 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 (when we weight by patent citations[35]). By contrast, $SPILLSIC$ is not significant in patents, productivity or R&D.

The pattern in Pharmaceuticals is similar, with significant technology spillovers and product market rivalry in the market value equation. Technology spillovers are also found in the production function and the patents equation when we weight by citations (intellectual property is particularly important in this industry[36]). As in the Computer hardware sector, the product market rivalry terms are insignificant in the patents, productivity and R&D equation. The results are slightly different in the Telecommunications equipment industry. We *do* observe significant technology spillover effects in the market value equation and cite-weighted patents equations, but $SPILLTECH$ is insignificant (although positive) in the productivity regressions. Similarly, $SPILLSIC$ is correctly signed (negative) but insignificant in the value equation and also insignificant in all other regressions.

[35] Weighting made no difference to the results in the overall sample, but seems to be more important in these high-tech sectors.

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

Overall, the results from these high-tech sectors indicate that our main results are present in precisely those R&D intensive industries where we would expect our theory to have most bite. There are two caveats. First, we do see some heterogeneity - although technology spillovers are found in all three sectors, significant product market rivalry effects of R&D are only evident in two of the three industries studied. Second, it is difficult to determine whether R&D is a strategic complement or substitute from these sectors as $SPILLSIC$ tends to be insignificant in the R&D and patent equations (whereas it was positive and significant in the main, pooled results), possibly due to the smaller sample size. We leave for future research a more detailed analysis of particular industries using our approach.

[**Tables 11, 12 about here**]

6. Policy Simulations

The model can also be used to evaluate the spillover effects of R&D subsidy policies. Throughout the policy experiments we consider a binary treatment (a firm is either eligible or not eligible) and assume that the proportionate increase in R&D is the same across all the eligible firms. We alter this proportionate increase so that it sums to the aggregate increase in the baseline case ($870m). This allows us to compare the cost effectiveness of alternative policies.

Four policy experiments are considered (Panel A, Table 12). For the first (row 1) each firm is given a one percent stimulus to R&D. Given the average R&D spending in the sample this "costs" $870 million. Working out the full amplification and dynamic effects in the model this generates an extra $755 million of R&D (for a total R&D increase of $1,625 million). This is associated with an extra $6,178 million in output. The other three experiments consider a stimulus of the same aggregate size ($870m) but distribute it in different ways.

The second experiment (row 2 in Panel A) is calibrated to a stylized version of the current U.S. R&D tax credit to determine the eligible group (40% of all firms in this case)[37]. This policy generates very similar spillovers for R&D and productivity as the overall R&D stimulus in row 1. The reason is that the firms eligible for the tax credit have very similar average linkages in the technology and product markets as those in the sample as a whole (compare rows 1 and 2 in Panel B, Table 12).

The third experiment gives an equi-proportionate increase in R&D only to firms below the median size, as measured by employment averaged over the 1990's (about 3,500 employees). The fourth experiment does the same for firms larger than the median size. Splitting by firm size is interesting because many R&D subsidy and other technology policies are targeted at small and medium sized enterprises.[38] These last two policy simulations show a striking result: the social returns, in terms of spillovers, of subsidizing "smaller" firms are much lower than from subsidizing larger firms. The stimulus to larger firms generates $6,287 million of extra output, as compared to only $3,745 million when the R&D subsidy is targeted on "smaller" firms. As Panel B shows, this difference arises because large firms are much more closely linked to other firms in technology space and thus generate (and benefit from) greater technology spillovers. The average value

[37] We keep to a simple structure in order to focus on the main policy features rather than attempt a detailed evaluation of actual existing tax credit systems (see Nick Bloom, Rachel Griffith and John Van Reenen, 2002, for a detailed analysis of fiscal incentives for R&D). We treat a firm as eligible in our simulation if it was eligible to receive any R&D tax credit for a majority of the 1990's.

[38] In practice, policies are typically targetted at firms much smaller than the median firm in our sample. We also tried conducting the experiment for the lowest and highest quartiles of the size distribution, but there was not enough R&D conducted by the lowest employment quartile to make the analysis sensible (i.e., the required percentage increase in their R&D was too large to justify the linear approximation of the model used for the simulations).

of $TECH$ for large firms is 0.129 as compared to 0.074 for "smaller" firms[39]. That is, smaller firms are more likely to operate in technology niches generating lower average spillovers.

This finding should caution against over-emphasis on small and medium sized firms by some policy makers. Of course, appropriate policy design would have to take into account many caveats in terms of the simplicity of the model (e.g. we have abstracted from credit constraints that might be worse for smaller firms).

7. 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 between 1980 and 2001 we show that both technology and product market spillovers operate, but social returns still exceed private returns to a large degree. We also find that R&D by product market rivals is (on average) a strategic complement for a firm's own R&D. Our findings are robust to alternative datasets and definitions of the distance metric. Using the model we evaluate the net spillovers (social returns) from three R&D subsidy policies which suggested that R&D policies that were tilted towards the smaller firms in our sample would be unwise if

[39] We were concerned that our econometric results may be under-estimating the spillovers of smaller firms. For example, relative to large firms, smaller companies may be less able to appropriate the benefits of technology spillovers, and thus be more likely to pass on technology spillovers to consumers in the form of lower prices. We tested this idea by interacting the size dummy with $SPILLTECH$ in the production function (Table 5, column 2). This interaction was negative, as expected, but small and insignificant (coefficient of -0.026 with a standard error of 0.019).

the objective is to redress market failures associated with technology spillovers.

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 using detailed industry-specific datasets. Second, it would be useful to develop and estimate more structural dynamic models of patent races. Finally, the semi-parametric approach in Joris Pinske, Margaret Slade and Craig Brett (2002) could be used to construct alternative spillover measures.

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 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 begin by choosing any *pair* of other firms, say j and k 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.

Case 1: $dr_{im} = 0$ implies $dr_j = -\frac{\theta_{ik}}{\theta_{ij}} dr_k$, with associated change in technology spillovers $dr_{i\tau} = (\omega_{ik} - \omega_{ij} \frac{\theta_{ik}}{\theta_{ij}}) dr_k \equiv \phi_{ijk} dr_k$.

Case 2: $dr_{i\tau} = 0$ implies $dr_j = -\frac{\omega_{ik}}{\omega_{ij}} dr_k$, with associated change in product market spillovers $dr_{im} = (\theta_{ik} - \theta_{ij} \frac{\omega_{ik}}{\omega_{ij}}) dr_k \equiv \lambda_{ijk} dr_k$.[40]

When constraining one spillover pool to be constant, the other pool can either increase or decline depending on the technology and product market distance weights.

Differentiating (A.5), allowing only r_i, r_j and r_k to change, we obtain:

$$\pi_{11} dr_i + \pi_{12}(\omega_{ij} dr_j + \omega_{ik} dr_k) + \pi_{13}(\theta_{ij} dr_j + \theta_{ik} dr_k) = 0$$

[40] We assume that the changes $dr_j = -\frac{\theta_{ik}}{\theta_{ij}} dr_k$ and $dr_j = -\frac{\theta_{ik}}{\theta_{ij}} dr_k$ do not violate the restriction $r_j \geq 0$.

The first bracketed expression is just $dr_{i\tau}$, and the second is zero by construction ($dr_{im} = 0$), so we get[41]

$$\frac{\partial r_i^*}{\partial r_{i\tau}} \mid_{dr_{im}=0} = -\frac{\pi_{12}}{\pi_{11}}. \tag{A.6}$$

Similarly, when we impose the constraint $dr_{i\tau} = 0$ we obtain:[42]

$$\frac{\partial r_i^*}{\partial r_{im}} \mid_{dr_{i\tau}=0} = -\frac{\pi_{13}}{\pi_{11}} \tag{A.7}$$

These are the key equations. Equation (A.6) says that if we make compensating changes in the R&D of two firms 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 of two firms 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

$$\frac{\partial V_i}{\partial r_{i\tau}} \mid_{dr_{im}=0} = \pi_2 \geq 0$$

$$\frac{\partial V_i}{\partial r_{im}} \mid_{dr_{i\tau}=0} = \pi_3 \leq 0$$

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.

These results easily generalize to the case where we allow any subset of firms to change so as to keep constant either $r_{i\tau}$,or r_{im}. Consider a subset denoted by $s \in S$ where $s \neq i$. Impose the constraint that $dr_{im} = \sum_{s\in S} \theta_{is} dr_s = 0$. The implied change in the technology spillovers is $dr_{i\tau} = \sum\limits_{s\in S} \omega_{is} dr_s$, which in general will differ from zero (it can be either positive or negative depending on the ω and θ weights).

[41] Another way of seeing this is to note that $\frac{\partial r_i^*}{\partial r_k} \mid_{dr_{im}=0} = -\frac{\phi_{ijk}\pi_{12}}{\pi_{11}}$, which implies the result in (A.6) since $dr_{i\tau} = \phi_{ijk} dr_k$.

[42] Again, we can also write $\frac{\partial r_i^*}{\partial r_k} \mid_{dr_{i\tau}=0} = -\frac{\lambda_{ijk}\pi_{13}}{\pi_{11}}$ which yields (A.7) since $dr_{im} = \lambda_{ijk} dr_k$.

Now totally differentiate the first order condition, allowing only r_s for $s \in S$ to change. 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 again get

$$\frac{\partial r_i^*}{\partial r_{i\tau}} |_{dr_{im}=0} = -\frac{\pi_{12}}{\pi_{11}}$$

By similar derivation we get

$$\frac{\partial r_i^*}{\partial r_{im}} |_{dr_{i\tau}=0} = -\frac{\pi_{13}}{\pi_{11}}$$

The effects on the value function follow immediately using the envelope theorem, as before.

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 of $\{dr_s\}$ 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 (see Section 2 for a non-tournament model). 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

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

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 $(n-1)h_2 F - 1 \leq 0$. That is, we require 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, $\frac{\partial V^0}{\partial k_m}|k_0 = 0$. As in the non-tournament case, $\frac{\partial r_0}{\partial r_m} > 0$ and $\frac{\partial V^0}{\partial r_m}|_{r_0} < 0$. The difference is that with a simple patent race, $\frac{\partial V^0}{\partial k_m}|_{k_0}$ is zero rather than negative because firms only race for a single patent.[43].

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

[43] 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.

strategic interaction in the product market, $\pi(\theta_0 k_0, x_0^*, x_m^*)$ does not vary with x_m and thus Π^0 do not depend on $\theta_m k_m$. We assume that $\Pi(\theta_0 k_0, \theta_m k_m)$ is increasing in $\theta_0 k_0$, decreasing in $\theta_m k_m$ and concave.

Stage 1

Firm $0's$ knowledge production function remains as

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

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

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

The first order conditions are

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

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

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:[44]

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

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:

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

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

In signing the above results, we use the fact that $V_{r_0 r_0} < 0, V_{\rho_0\rho_0} < 0, V_{\rho_0 r_0} > 0$ (provided Π_{11} is 'sufficiently small') and $A = V_{r_0 r_0}V_{\rho_0\rho_0} - V_{r_0\rho_0}^2 > 0$ by the second

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

order conditions, and the other cross partials: $V_{r_0r_\tau} = \frac{\phi_{12}}{\phi_1} + \theta_0^2\phi_1^0\phi_2^0\Pi_{11}; V_{r_0r_m} = \theta_0\theta_m\phi_1^0\phi_1^m\Pi_{12}, V_{r_0\rho_\tau} = 0; V_{r_0\rho_m} = (\lambda-1)\theta_0k_m\phi_1^0\Pi_{12};$

$V_{\rho_0r_\tau} = (\lambda-1)\theta_0k_0\phi_2^0\Pi_{11}; V_{\rho_0r_m} = (\lambda-1)k_0\theta_m\phi_1^m\Pi_{12}; V_{\rho_0\rho_\tau} = 0$; and $V_{\rho_0\rho_m} = (\lambda-1)^2k_0k_m\phi_2^0\Pi_{12}$.

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 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.[45]

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

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

Compustat accounting data to the USPTO data between 1970 to 1999[46], 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.

B.2. The Bureau Van Dijk (BVD) Database

Since the BVD dataset has not been widely used by economists we describe it in more detail than Compustat.

B.2.1. The ICARUS and AMADEUS Datasets

The BVD sales breakdown was calculated using the employment breakdown across primary and secondary four digit industry classes for enterprises in North America (US and Canada) and Europe[47]. BVD provides information on the employment in the subsidiaries of our Compustat firms which can then be used to allocate their activities to standard industrial classification classes. BVD sells a database called ICARUS which contains 1.8 million enterprise level records for the US and Canada containing information on sales, employment, industry and ownership. It

[46] We dropped pre-1970 data as being too outdated for our 1980s and 1990s accounts data.
[47] We thank Kevin Krabbenhoeft for his excellent help with this.

is drawn from the complete North American Dunn and Bradstreet database (of over ten million enterprises) selecting all enterprises that have either twenty or more employees or $5 million or more in sales. The data is cross-sectional and is continuously updated. We downloaded the complete database in September 2005. BVD also sells a database called AMADEUS which contains eight million enterprise level records for Europe (broadly defined to include Israel, Russia, Turkey, etc.). This contains cross-sectional information on employment, industry sector and ownership (plus various types of accounting information). It is constructed from country-specific registries of companies. For example all corporate entities in Britain have to lodge basic accounts with UK Company House in the UK (i.e. privately as well as publicly listed firms). We used the May 2006 AMADEUS disk which contains industry sector records primarily from 2004 and 2005.

B.2.2. Calculation of the Sales Breakdown figures

All BVD databases use a common global identification system so that ownership structures can be easily constructed across countries. The ICARUS and AMADEUS databases were merged into the Compustat database in three stages. First, all enterprises were accorded an ultimate global parent name, a BVD identification number and (if relevant) a ticker symbol. Second, the population of ultimate parents was matched into the Compustat database. This was done first using ticker symbols where these were provided by BVD, then for the unmatched firms using company names after standardizing certain generic components (for example standardizing "Co.", "Co" and "company" to "Company"), and finally by manual inspection for any remaining unmatched firms. Third, the BVD enterprise-level information was linked to Compustat through the ultimate parent link to Compustat.

Activity in each enterprise was then allocated across industries using the four digit industry information. In ICARUS firms report one primary four digit industry code and an ordered set of up to six secondary four digit industry codes. Employment activity was allocated assuming 75% of activity was in the primary industry code, 75% of the remainder in the secondary code, 75% of this remainder in the tertiary industry code and so on, with the final industry code containing 100% of the ultimate residual. In AMADEUS 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 summed across all industry codes in every enterprise in Europe and the US owned by the ultimate Compustat parent to compute a four digit industry breakdown of activity.

B.2.3. 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 reason appears to be that larger R&D intensive Compustat firms are less likely to have died, been taken over or changed their name between 2001 and 2005 (the gap between the last year of our Compustat sample and the timing of the BVD data).

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.2.4. 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.

B.3. Other variables

The book value of capital is the net stock of property, plant and equipment (Compustat Mnemonic PPENT); Employment is the number of employees (EMP). R&D (XRD) is used to create R&D capital stocks calculated using a perpetual inventory method with a 15% depreciation rate (following inter alia Hall et al, 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 and $\delta = 0.15$. We use sales as our output measure (SALE). Material inputs were constructed following the method in Bresnahan et al. (2002). We start with costs of good sold (COGS) less depreciation (DP) less labor costs (XLR). For firms who do not report labor expenses we use average wages and benefits at the four digit industry level (Erik Bartelsman, Randy Becker and Wayne Gray, 2000, until 1996 and then Census Average Production Worker Annual Payroll by four digit NAICS code afterwards) and multiply this by the firm's reported employment level. This constructed measure of materials is highly correlated with independent industry-level materials measures. Obviously there are problems with this measure of materials (and therefore value added) because we do not have a firm specific wage bill for most firms which is why we focus on the real sales (rather than value added) based production functions. Industry price deflators were taken from Bartelsman et al (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 (Mnemonics MKVAF, PSTK, DT and ACT). Book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles other than R&D (Mnemonics PPENT, INVT, IVAEQ, IVAO and INTAN). Tobin's Q was winsorized by setting it to 0.1 for values below 0.1 and at 20 for values above 20 (see Jenny Lanjouw and Mark Schankerman (2004)).

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.4. Specific High Tech Industry Breakdown

In Table 11 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).

C. Alternative Distance Metrics

Some general issues regarding construction of spillover measures are discussed in section 3 (especially 3.4). In this Appendix we offer one justification of the $SPILLSIC^A$ measure in the first sub-section (C.1) and then adapt the Ellison-Glaeser (1997) co-agglomeration/spillover measure in the next sub-section (C.2).

C.1. 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:

$$Q_i^l = \alpha \sum_{j,j \neq i} \omega_j^l r_j \tag{C.1}$$

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:

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

where h_i^l are the appropriate aggregation weights. Substituting (C.2) into (C.1) gives

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

We write this compactly as:

$$Q_i = \alpha \sum_{j,j\neq i} d_{ij} r_j \tag{C.4}$$

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 therefore different measures of $SPILLSIC$.

For the weight on h_i^l it seems very 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:

$$Q_i = \alpha SPILLSIC_i \tag{C.5}$$

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.3) we then obtain, $SPILLSIC_i^A$

$$SPILLSIC_i^A = \sum_{j,j\neq i} \left(\sum_l s_i^l s_j^l \right) r_j = \sum_{j,j\neq i} SIC_{ij}^A r_j \tag{C.6}$$

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 10 Panels B and C. The results are robust to this experiment.

C.2. The Ellison-Glaeser (1997) Co-agglomeration measure

Ellison and Glaeser (1997, henceforth EG) propose measures of agglomeration and co-agglomeration. In their model they are interested in reasons why some industries appear to be concentrated in geographical areas. One reason for this concentration is that some areas have "natural advantages" such as the fact that shipbuilding and tuna canning industries are co-located in areas near coastlines. But another reason may be spillovers between geographically local plants generating an incentive for firms to locate their plants in similar places even in the absence of natural advantage. They propose a simple theoretical model which generates an equilibrium degree of agglomeration (the regional concentration of industries) and co-agglomeration (the tendency of different industries to co-locate together) and propose empirical measures to consistently estimate the theoretical concepts.

We can construct analogous measure for technological distance instead of geographical distance. Consider two firms (instead of two industries in EG) deciding which technology classes to locate their innovations (instead of their plants in EG). If there are potential spillovers between the inventions of the two firms we would expect to see their innovations (measured by patents in our case) to be clustered in the same technological classes. EG offer a theoretical model to justify their empirical spillover/co-agglomeration measures. Unfortunately, their procedure will not work for $SPILLSIC$ as their model assumes that (at least potentially) there is a *positive* profitability benefit of having another firm located close. In the case of product market rivalry this will be a negative effect as having more plants of a rival to firm i close will hurt not help firm i's profitability.

The EG co-agglomeration measure can be adapted to a distance metric between firm i and firm j as:

$$\begin{aligned}\gamma_{ij} &= (1-w_i^2-w_j^2)^{-1}\frac{\sum_\tau (T_{i\cup j,\tau}-x_\tau)^2}{1-\sum_\tau x_\tau^2} - w_i^2\frac{\sum_\tau (T_{i\tau}-x_\tau)^2}{1-\sum_\tau x_\tau^2} - w_j^2\frac{\sum_\tau (T_{j\tau}-x_\tau)^2}{1-\sum_\tau x_\tau^2} \\ &= \left(\frac{1-\sum_k x_\tau^2}{1-w_i^2-w_j^2}\right)\left(\sum_\tau (T_{i\cup j,\tau}-x_\tau)^2 - w_i^2\sum_\tau (T_{i\tau}-x_\tau)^2 - w_j^2\sum_\tau (T_{j\tau}-x_\tau)^2\right)\end{aligned}$$

where $T_{i\tau}$ is the share of patents of firm i in technology class τ, x_τ is the aggregate share of patents in technology class τ, $T_{i\cup j,\tau}$ is the patent share of the hypothetical combination of firms i and j in technology class τ and $w_i(w_j)$ is the weight of firm i's (j's) patents in the combined firm of i and j (i.e. $w_i = PATENTS_i/(PATENTS_i + PATENTS_j) = 1 - w_j$.

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 0.13 - see Table 12). 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 0.05 - see Table 12). 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 Mototrola 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. Policy Experiments

The general specification of the empirical model can be written

$$\begin{aligned}
\ln(R/Y)_{it} &= \widetilde{\alpha}_1 \ln(R/Y)_{it-1} + \widetilde{\alpha}_2 \ln \sum_{j \neq i} TECH_{ij} G_{j,t-1} + \widetilde{\alpha}_3 \ln \sum_{j \neq i} SIC_{ij} G_{j,t-1} \\
&\quad + \widetilde{\alpha}_4 X_{1,it} \\
\ln P_{it} &= \widetilde{\beta}_0 \ln P_{it-1} + \widetilde{\beta}_1 \ln G_{it-1} + \widetilde{\beta}_2 \ln \sum_{j \neq i} TECH_{ij} G_{j,t-1} + \widetilde{\beta}_3 \ln \sum_{j \neq i} SIC_{ij} G_{j,t-1} \\
&\quad + \widetilde{\beta}_4 X_{2it} + \widetilde{\beta}_5 \ln Y_{i,t-1} \\
\ln(V/A)_{it} &= \widetilde{\gamma}_1 \ln(G/A)_{it} + \widetilde{\gamma}_2 \ln \sum_{j \neq i} TECH_{ij} G_{j,t-1} + \widetilde{\gamma}_3 \ln \sum_{j \neq i} SIC_{ij} G_{j,t-1} + \widetilde{\gamma}_4 X_{3,it} \\
\ln Y_{it} &= \widetilde{\varphi}_1 \ln G_{it} + \widetilde{\varphi}_2 \ln \sum_{j \neq i} TECH_{ij} G_{j,t-1} + \widetilde{\varphi}_3 \ln \sum_{j \neq i} SIC_{ij} G_{j,t-1} + \widetilde{\varphi}_4 X_{4,it}
\end{aligned}$$

where R is the flow of R&D expenditures, Y is output, G is the R&D stock, P is patent flow, V/A is Tobin's Q, and X_1, X_2, X_3 and X_4 are vectors of control variables (that for ease of exposition we treat as scalars). We actually use a sixth order series in $\ln(G/A)$,but suppress that here for notational simplicity.

We examine the long run effects in the model, setting $R_{it} = R_{it-1}, Y_{it} = Y_{it-1}, P_{it} = P_{it-1}$, and $G_j = \frac{R_j}{r+\delta}$ where r is the discount rate and δ is the depreciation rate used to construct G. Then the model is

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

$$\begin{aligned}
\ln P_i &= \beta_1 \ln R_i + \beta_2 \ln \sum_{j \neq i} TECH_{ij} R_j + \beta_3 \ln \sum_{j \neq i} SIC_{ij} R_j \\
&\quad + \beta_4 X_{2i} + \beta_5 \ln Y_{it}
\end{aligned} \tag{E.2}$$

$$\ln(V/A)_i = \gamma_1 \ln(R/A)_i + \gamma_2 \ln \sum_{j \neq i} TECH_{ij} R_j + \gamma_3 \ln \sum_{j \neq i} SIC_{ij} R_j + \gamma_4 X_{3i} \tag{E.3}$$

$$\ln Y_{it} = \varphi_1 \ln R_i + \varphi_2 \ln \sum_{j \neq i} TECH_{ij} R_j + \varphi_3 \ln \sum_{j \neq i} SIC_{ij} R_j + \varphi_4 X_{4i} \tag{E.4}$$

where $\alpha_k = \frac{\widetilde{\alpha}_k}{(1-\widetilde{\alpha}_1)}$, $\beta_k = \frac{\widetilde{\beta}_k}{(1-\widetilde{\beta}_1)}$, $\gamma_k = \widetilde{\gamma}_k$ and $\varphi_k = \widetilde{\varphi}_k$.

We then solve out the cross equation links with Y_{it} by substituting equation (E.4) into equations (E.1) and (E.2). This yields

$$\ln R_i = \alpha_2' \ln \sum_{j\neq i} TECH_{ij} R_j + \alpha_3' \ln \sum_{j\neq i} SIC_{ij} R_j + \alpha_4' X_{1i} \tag{E.5}$$

$$\ln P_i = \beta_1' \ln R_i + \beta_2' \ln \sum_{j\neq i} TECH_{ij} R_j + \beta_3' \ln \sum_{j\neq i} SIC_{ij} R_j + \beta_4' X_{2i} \tag{E.6}$$

$$\begin{aligned} \ln(V/A)_i &= \gamma_1 \ln(R/A)_i + \gamma_2 \ln \sum_{j\neq i} TECH_{ij} R_j + \gamma_3 \ln \sum_{j\neq i} SIC_{ij} R_j \\ &\quad + \gamma_4 X_{3i} \end{aligned} \tag{E.7}$$

$$\begin{aligned} \ln Y_{it} &= \varphi_1 \ln R_i + \varphi_2 \ln \sum_{j\neq i} TECH_{ij} R_j + \varphi_3 \ln \sum_{j\neq i} SIC_{ij} R_j \\ &\quad + \varphi_4 X_{4i} \end{aligned} \tag{E.8}$$

where $\alpha_i' = \frac{\alpha_i + \alpha_5 \varphi_i}{1-\alpha_5\varphi_1} = \frac{\widetilde{\alpha}_i}{(1-\varphi_1)(1-\widetilde{\alpha}_1)} + \frac{\varphi_i}{(1-\varphi_1)}$ and $\beta_i' = \beta_i + \beta_5 \varphi_i = \frac{\widetilde{\beta}_i + \widetilde{\beta}_5 \varphi_i}{(1-\widetilde{\beta}_1)}$.

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

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

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

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

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

Define

$$\lambda_i = \alpha_2' a_i + \alpha_3' c_i$$

$$\theta_{ij} = \alpha_2' b_{ij} + \alpha_3' d_{ij}$$

Using these approximations, we can write the R&D equation (E.5)as

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

Let $\lambda, \ln R$ and X be Nx1 vectors, and define the NxN matrix

$$H = \begin{pmatrix} 0 & \theta_{12} & \theta_{13} & . & . & \theta_{iN} \\ \theta_{21} & 0 & \theta_{23} & & & \theta_{2N} \\ \theta_{31} & \theta_{32} & 0 & \theta_{34} & . & \theta_{3N} \\ . & & & & & . \\ , & & & & & . \\ \theta_{N1} & \theta_{N2} & . & . & . & 0 \end{pmatrix}$$

Then the R&D equation can be expressed in matrix form

$$\begin{aligned} \ln R &= \Omega^{-1}\lambda + \alpha_4' \Omega^{-1} X_1 \\ &\Longrightarrow \\ d \ln R &= \Omega^{-1} \alpha_4' dX_1 \end{aligned}$$

where $\Omega = I - H$.

E.1. Deriving the Amplification Effects

E.1.1. R&D equation

Using the restriction $\sum_{j \neq i} b_{ij}$, it can be shown that $H \times i = \alpha_2' + \alpha_3'$ where i is a column vector of ones. Thus $\Omega \times i = 1 - \alpha_2' + \alpha_3'$, so the macro R&D response to a unit stimulus to R&D of each firm (equal to $\alpha_4' dX_1$) is

$$\Omega^{-1} \times i = \frac{1}{1 - \alpha_2' - \alpha_3'}$$

In the absence of technology and product market spillovers, R&D would increase by one percent. Thus we define the amplification effect as $\frac{1}{1-\alpha_2'-\alpha_3'} - 1$.

E.1.2. Patents equation

Using the approximations above, the patents equation (E.6) is[48]

$$\ln P_i = \beta_1' \ln R_i + \sum_{j \neq i} \rho_{ij} \ln R_j + \beta_4' X_{2i}$$

where $\rho_{ij} = \beta_2' b_{ij} + \beta_3' d_{ij}$. By similar reasoning, we define the NxN matrix

$$G = \begin{pmatrix} 0 & \rho_{12} & \rho_{13} & . & . & \rho_{iN} \\ \rho_{21} & 0 & \rho_{23} & & & \rho_{2N} \\ \rho_{31} & \rho_{32} & 0 & \rho_{34} & . & \rho_{3N} \\ . & & & & & . \\ , & & & & & . \\ \rho_{N1} & \rho_{N2} & . & . & . & 0 \end{pmatrix}$$

Letting $d\ln R$ and $d\ln P$ be $Nx1$ vectors, we get

$$d\ln P = \beta_1' d\ln R + [G \times d\ln R]$$

Using the result from the R&D amplification effect $d\ln R = \frac{1}{1-\alpha_2'+\alpha_3'} \times i$, we get the macro response of patents to a unit stimulus to R&D of each firm

$$\begin{aligned} d\ln P &= \frac{1}{1-\alpha_2'-\alpha_3'}(\beta_1' \times i \times i' + G) \times i \\ &= \frac{1}{1-\alpha_2'-\alpha_3'}(\beta_1' + \beta_2' + \beta_3') \times i \end{aligned}$$

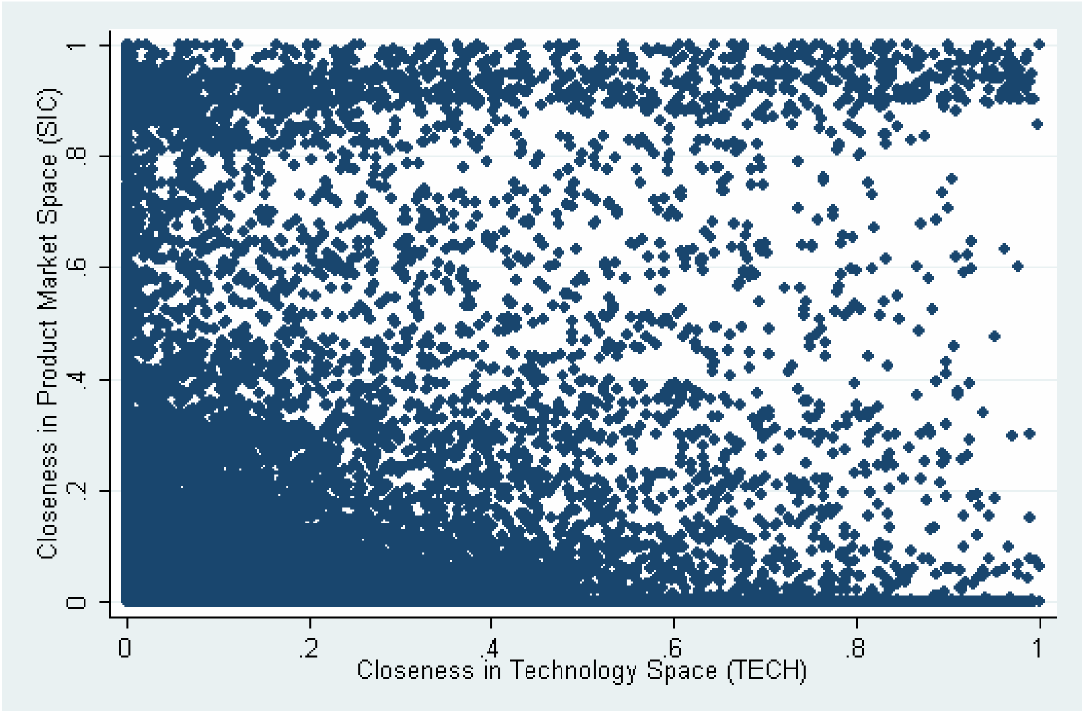
Thus the amplification effect on patents equals $\frac{1}{1-\alpha_2'-\alpha_3'}(\beta_1' + \beta_2' + \beta_3') - \beta_1'$.

E.1.3. Tobin's-Q and productivity equations

The calculations are completely analogous to those for the patent equation. For brevity, we do not repeat the details here.

[48] In this experiment we assume that the only forcing variable is X_1. If X_2 in the patents equation is the same as X_1 (e.g. industry sales), then we need to add the direct effect of the change in X_1 on patents as well as the induced effect via R&D.

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 OVER TECHNOLOGICAL SPILLOVERS AND STRATEGIC COMPLEMENTARITY/SUBSTITUTABILITY OF R&D

(1) Equation	(2) Comparative static prediction	(3) Empirical counterpart	(4) No Technology Spillovers No Product Market Rivalry	(5) No Technology Spillovers Strategic Complements	(6) No Technology Spillovers Strategic Substitutes	(7) Technology Spillovers Strategic Complements	(8) Technology Spillovers Strategic Substitutes
Market value	$\partial V_0/\partial r_\tau$	Market value with SPILLTECH	Zero	Zero	Zero	Positive	Positive
Market value	$\partial V_0/\partial r_m$	Market value with SPILLSIC	Zero	Negative	Negative	Negative	Negative
Patents (or productivity)	$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Zero	Zero	Zero	Positive	Positive
Patents (or productivity)	$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	Zero	Zero	Zero	Zero
R&D	$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Zero	Zero	Zero	Ambiguous	Ambiguous
R&D	$\partial r_0/\partial r_m$	R&D with SPILLSIC	Zero	Positive	Negative	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**	**Mean**	**Median**	**Standard deviation**
Tobin's Q	V/A	2.36	1.41	2.99
Market value	V	3,913	412	16,517
R&D stock	G	605	28.7	2,722
R&D stock/fixed capital	G/A	0.48	0.17	0.95
R&D flow	R	104	4.36	469
Technological spillovers	SPILLTECH	22,419	17,914	17,944
Product market rivalry	SPILLSIC	6,494	2,006.8	10,114
Patent flow	P	16.2	1	75
Sales	Y	2,879	456	8,790
Fixed capital	A	1,346	122	4,720
Employment	N	18,379	3,839	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

Dependent variable: Ln (V/A)	(1) No individual Effects	(2) Fixed Effects	(3) Fixed Effects (drop SPILLSIC)	(4) Fixed Effects (drop SPILLTECH)
Ln($SPILLTECH_{t-1}$)	-0.042	0.242	0.186	
	(0.012)	(0.105)	(0.100)	
Ln($SPILLSIC_{t-1}$)	0.051	-0.072		-0.050
	(0.007)	(0.032)		(0.031)
Ln(Industry $Sales_t$)	0.425	0.300	0.294	0.305
	(0.068)	(0.044)	(0.044)	(0.044)
Ln(Industry $Sales_{t-1}$)	-0.503	-0.173	-0.178	-0.166
	(0.067)	(0.045)	(0.045)	(0.045)
Polynomial terms in lagged (R&D Stock/Capital Stock)				
Ln(R&D Stock/Capital $Stock)_{t-1}$	0.842	0.799	0.794	0.799
	(0.154)	(0.197)	(0.198)	(0.198)
$[$Ln(R&D Stock/Capital $Stock)_{t-1}]^2$	-0.172	-0.384	-0.377	-0.374
	(0.215)	(0.222)	(0.222)	(0.222)
$[$Ln(R&D Stock/Capital $Stock)_{t-1}]^3$	-0.024	0.120	0.116	0.115
	(0.111)	(0.103)	(0.103)	(0.104)
$[$Ln(R&D Stock/Capital $Stock)_{t-1}]^4$	-0.013	-0.021	-0.020	-0.020
	(0.025)	(0.022)	(0.022)	(0.022)
$[$Ln(R&D Stock/Capital $Stock)_{t-1}]^5$	-0.002	-0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
$[$Ln(R&D Stock/Capital $Stock)_{t-1}]^6$	0.006 [a]	-0.007[a]	-0.006[a]	-0.006 [a]
	(0.009)	(0.008)	(0.008)	(0.008)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	Yes
No. Observations	9,944	9,944	9,944	9,944

[a] coefficient and standard error have been multiplied by 100

Notes: Tobin's Q = V/A is defined as the market value of equity plus debt, divided by the stock of fixed capital. The equations are estimated by OLS (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 equals zero.

TABLE 4 -
COEFFICIENT ESTIMATES FOR THE PATENT EQUATION

Dependent variable: Patent Count	(1) No Initial Conditions: Static	(2) Initial Conditions: Static	(3) Initial Conditions: Dynamics
$Ln(SPILLTECH)_{t-1}$	0.406	0.295	0.192
	(0.086)	(0.066)	(0.038)
$Ln(SPILLSIC)_{t-1}$	0.037	0.051	0.032
	(0.031)	(0.029)	(0.016)
$Ln(R\&D\ Stock)_{t-1}$	0.492	0.280	0.104
	(0.044)	(0.046)	(0.027)
$Ln(Sales)_{t-1}$	0.340	0.259	0.138
	(0.052)	(0.048)	(0.027)
$Ln(Patents)_{t-1}$			0.550
			(0.026)
Pre-sample fixed effect		0.452	0.176
		(0.050)	(0.028)
Over-dispersion (alpha)	0.955	0.815	0.402
	(0.062)	(0.046)	(0.029)
Year dummies	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes
4 digit industry dummies	Yes	Yes	Yes
No. Observations	9,023	9,023	9,023
Log Pseudo Likelihood	-20,499	-20,116	-18,636

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 four digit industry dummies 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 initial conditions effects in column (3) is 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

Dependent variable: Ln(Sales)	(1) No Fixed Effects	(2) Fixed Effects	(3) Fixed Effects
Ln(SPILLTECH) $_{t-1}$	-0.030	0.103	0.111
	(0.009)	(0.046)	(0.045)
Ln(SPILLSIC) $_{t-1}$	-0.016	0.010	
	(0.004)	(0.012)	
Ln(Capital) $_{t-1}$	0.286	0.161	0.161
	(0.009)	(0.012)	(0.012)
Ln(Labour) $_{t-1}$	0.650	0.631	0.631
	(0.012)	(0.015)	(0.015)
Ln(R&D Stock) $_{t-1}$	0.059	0.044	0.045
	(0.005)	(0.007)	(0.007)
Ln(Industry Sales) $_{t}$	0.230	0.200	0.201
	(0.040)	(0.021)	(0.021)
Ln(Industry Sales) $_{t-1}$	-0.118	-0.039	-0.038
	(0.040)	(0.022)	(0.022)
Year dummies	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes
No. Observations	10,009	10,009	10,009
R^2	0.948	0.990	0.990

Notes: Estimation is by OLS. 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.

TABLE 6 –
COEFFICIENT ESTIMATES FOR THE R&D EQUATION

Dependent variable: ln(R&D/Sales)	(1) No Fixed Effects	(2) Fixed Effects	(3) No Fixed Effects+ Dynamics	(4) Fixed Effects + Dynamics
$Ln(SPILLTECH)_{t-1}$	0.092	0.117	0.001	-0.036
	(0.017)	(0.074)	(0.004)	(0.040)
$Ln(SPILLSIC)_{t-1}$	0.371	0.088	0.017	0.033
	(0.013)	(0.035)	(0.002)	(0.019)
$Ln(R\&D/Sales)_{t-1}$			0.969	0.681
			(0.004)	(0.015)
$Ln(Industry Sales)_{t}$	0.523	-0.036	-0.023	-0.031
	(0.082)	(0.029)	(0.022)	(0.022)
$Ln(Industry Sales)_{t-1}$	-0.893	0.065	0.009	0.078
	(0.081)	(0.031)	(0.022)	(0.022)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	Yes
No. Observations	8,579	8,579	8,387	8,387
R^2	0.776	0.973	0.945	0.986

Notes: Estimation is by OLS. Standard errors (in brackets) are robust to arbitrary heteroskedacity and serial correlation using Newey-West corrected standard errors. The sample includes only firms which performed R&D continuously in at least two adjacent years.

TABLE 7 –
COMPARISON OF EMPIRICAL RESULTS TO MODEL WITH TECHNOLOGICAL SPILLOVERS AND STRATEGIC COMPLEMENTARITY

	Partial correlation of:	*Theory*	*Empirics*	*Consistency?*
$\partial V_0/\partial r_\tau$	Market value with SPILLTECH	Positive	0.242**	Yes
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	-0.072**	Yes
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Positive	0.192**	Yes
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero[a]	0.032*	No [a]
$\partial y_0/\partial r_\tau$	Productivity with SPILLTECH	Positive	0.103**	Yes
$\partial y_0/\partial r_m$	Productivity with SPILLSIC	Zero	0.010	Yes
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Ambiguous	-0.036	-
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Positive	0.033*	Yes

[a] The extension of the model in Appendix A3 that allows for strategic patenting generates a positive effect under strategic complementarity.

Notes: The theoretical predictions are for the case of technological spillovers with product market rivalry (strategic complements and non-tournament R&D) - this is column (7) of Table 1. The empirical results are from the most demanding specifications for each of the dependent variables (i.e. dynamic fixed effects for patents and R&D, and fixed effects for market value). ** 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 –
SPILLOVER AND TOTAL EFFECTS OF AN R&D SHOCK

	Variable	Amplification Mechanism	(1) Autarky Effect	(2) Amplification Effect	(3) Total Effect (Amplification + Autarky)
1	**R&D**		1	0.242	1.242
				(0.059)	(0.053)
2	**Patents**	TECH, SIC and R&D	0.231	0.562	0.793
			(0.032)	(0.100)	(0.082)
3	**Market Value**	TECH, SIC and R&D	0.726	0.248	0.975
			(0.161)	(0.111)	(0.208)
4	**Productivity**	TECH, SIC and R&D	0.045	0.124	0.169
			(0.007)	(0.049)	(0.049)

Notes: Calculated in response to a 1% direct stimulus to R&D in all firms – see text. All numbers are percentages. Results are calculated using preferred estimation results (i.e. Table 3 column (2), Table 4 column (3), Table 5 column (3) Table 6 column (4)). Standard errors in brackets calculated using the delta method.

"Autarky effect" (in column (1)) refers to the impact on the outcomes solely from the firm's initial increase in R&D. "Amplification Effects" (in column (2)) reports the *additional* impact from product market and technology space spillovers. "Total effect" (column (3)) reports the total effect from summing autarky and spillover effects (i.e. column (1) plus column (2)).

TABLE 9 – ALTERNATIVE CONSTRUCTION OF SPILLSIC USING BVD INFORMATION INSTEAD OF COMPUSTAT SEGMENT DATASET

Dependent variable:	(1) Tobin's Q	(2) Patents	(3) Ln(Real Sales)	(4) Ln(R&D/Sales)
	Fixed Effects	Initial Conditions: Dynamics	Fixed effects	Fixed Effects + Dynamics
Ln($SPILLTECH_{t-1}$)	0.310	0.185	0.100	-0.048
	(0.108)	(0.049)	(0.052)	(0.041)
Ln($SPILLSIC_{t-1}$)	-0.060	0.031	0.001	0.048
	(0.034)	(0.014)	(0.014)	(0.017)
Ln(Industry $Sales_t$)	0.235		0.194	-0.049
	(0.049)		(0.025)	(0.026)
Ln(Industry $Sales_{t-1}$)	-0.142		-0.042	0.094
	(0.050)		(0.026)	(0.026)
Ln(R&D Stock) $_{t-1}$		0.118	0.057	
		(0.032)	(0.008)	
Ln(R&D/Sales) $_{t-1}$				0.697
				(0.017)
Ln(Capital) $_{t-1}$			0.169	
			(0.014)	
Ln(Labor) $_{t-1}$			0.625	
			(0.018)	
Ln(R&D Stock/Capital Stock)$_{t-1}$	0.901			
	(0.221)			
[Ln(R&D Stock/Capital Stock)$_{t-1}$]^2	-0.393			
	(0.244)			
[Ln(R&D Stock/Capital Stock)$_{t-1}$]^3	0.106			
	(0.111)			
[Ln(R&D Stock/Capital Stock)$_{t-1}$]^4	-0.017			
	(0.023)			
[Ln(R&D Stock/Capital Stock)$_{t-1}$]^5	0.002			
	(0.002)			
[Ln(R&D Stock/Capital Stock)$_{t-1}$]^6	-0.006 [a]			
	(0.008)			
Ln(Sales)$_{t-1}$		0.107		
		(0.032)		
Ln(Patents)$_{t-1}$		0.545		
		(0.029)		
Pre-sample fixed effect		0.203		
		(0.035)		
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes (BGVR)	Yes	Yes
No. Observations	7,269	6,699	7,364	6,325

[a] coefficient and standard error have been multiplied by 10

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 (3); 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 (4).

TABLE 10 – ALTERNATIVE CONSTRUCTION OF SPILLOVER VARIABLES

A. Baseline (Summarized from Tables 3-6 above)

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Patents	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.242	0.192	0.103	-0.036
	(0.105)	(0.038)	(0.046)	(0.040)
$Ln(SPILLSIC)_{t-1}$	-0.072	0.032	0.010	0.033
	(0.032)	(0.016)	(0.012)	(0.019)
Lagged dependent variable		0.402		0.681
		(0.029)		(0.015)
Observations	9,944	9,023	10,009	8,387

B. Alternative Based on SPILLSIC^{A} (and SPILLTECH unchanged)

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Patents	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.239	0.192	0.106	-0.041
	(0.104)	(0.038)	(0.046)	(0.040)
$Ln(SPILLSIC)_{t-1}$	-0.068	0.049	0.004	0.036
	(0.032)	(0.017)	(0.010)	(0.019)
Lagged dependent variable		0.550		0.681
		(0.026)		(0.015)
Observations	9,958	9,046	10,023	8,387

C. Alternative Based on SPILLSIC^{A} and SPILLTECH^{A}

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Patents	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.188	0.241	0.085	-0.032
	(0.193)	(0.049)	(0.040)	(0.036)
$Ln(SPILLSIC)_{t-1}$	-0.069	0.041	0.004	0.036
	(0.032)	(0.017)	(0.012)	(0.019)
Lagged dependent variable		0.540		0.681
		(0.026)		(0.015)
Observations	9,958	9,046	10,023	8,387

D. Alternative Based on SPILLTECH^{EG} (see Ellison-Glaeser, 1997)

	(1)	(2)	(3)	(4)
Dependent variable	Tobin's Q	Patents	Real Sales	R&D/Sales
$Ln(SPILLTECH)_{t-1}$	0.886	0.653	0.061	-0.167
	(0.184)	(0.273)	(0.075)	(0.075)
$Ln(SPILLSIC)_{t-1}$	-0.076	0.039	0.017	0.035
	(0.031)	(0.010)	(0.013)	(0.017)
Lagged dependent variable		0.637		0.680
		(0.027)		(0.015)
Observations	9,944	9,023	10,009	8,387

E. 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	0.223	0.059	0.023
	(0.062)	(0.032)	(0.025)	(0.029)
Ln(SPILLSIC)$_{t-1}$	-0.063	0.023	0.002	0.021
	(0.033)	(0.017)	(0.013)	(0.019)
Lagged dependent variable		0.547		0.680
		(0.026)		(0.015)
Observations	9,848	8,923	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). 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 (3); 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 (4). 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 D uses a variant of the the Ellison-Glaeser (1997) co-agglomeration measure of distance for *SPILLTECH* (Panel E uses a more disaggregated version of technology classes, $SPILLTECH^{TFK}$, as suggested by Thompson and Fox-Kean, 2005). See section 3.4 and Appendix C for more details.

TABLE 11 – ECONOMETRIC RESULTS FOR SPECIFIC HIGH TECH INDUSTRIES

A. Computer Hardware

Dependent variable	(1) Tobin's Q	(2) Patents	(3) Cite-weighted patents	(4) Real Sales	(5) R&D/Sales
$\ln(\text{SPILLTECH})_{t-1}$	1.302	0.013	0.427	0.457	-0.158
	(0.613)	(0.158)	(0.176)	(0.222)	(0.164)
$\ln(\text{SPILLSIC})_{t-1}$	-0.472	0.532	-0.193	-0.046	0.091
	(0.159)	(0.433)	(0.525)	(0.226)	(0.095)
Lagged dependent variable		0.696	0.488		0.648
		(0.065)	(0.088)		(0.059)
Observations	358	277	277	343	388

B. Pharmaceuticals

Dependent variable	(1) Tobin's Q	(2) Patents	(3) Cite-weighted patents	(4) Real Sales	(5) R&D/Sales
$\ln(\text{SPILLTECH})_{t-1}$	1.611	-0.273	1.056	0.638	0.154
	(0.674)	(0.326)	(0.546)	(0.279)	(0.243)
$\ln(\text{SPILLSIC})_{t-1}$	-1.324	-0.106	-0.089	-0.396	0.359
	(0.612)	(0.194)	(0.174)	(0.339)	(0.532)
Lagged dependent variable		0.218	0.269		0.660
		(0.091)	(0.089)		(0.117)
Observations	334	265	265	313	381

C. Telecommunication Equipment

Dependent variable	(1) Tobin's Q	(2) Patents	(3) Cite-weighted patents	(4) Real Sales	(5) R&D/Sales
$\ln(\text{SPILLTECH})_{t-1}$	2.299	0.290	0.651	0.477	0.217
	(0.869)	(0.175)	(0.364)	(0.339)	(0.208)
$\ln(\text{SPILLSIC})_{t-1}$	-0.118	0.064	-0.025	0.154	-0.049
	(0.456)	(0.073)	(0.217)	(0.182)	(0.085)
Lagged dependent variable		0.645	0.476		0.598
		(0.093)	(0.098)		(0.059)
Observations	405	353	353	390	429

Notes: Each Panel (A, B, C) contains the results from estimating 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; Patents (column 2) corresponds to column (3) of Table 4; cite-weighted patents (column 3) is identical to the previous column but replaces all patent counts with their forward cite weighted equivalents; real sales (column 4) corresponds to column (2) of Table 5; R&D/Sales (column (5)) corresponds to column (4) of Table 6.

TABLE 12 – POLICY SIMULATIONS: SPILLOVER IMPACTS ACROSS DIFFERENT GROUPS OF FIRMS

Panel A

Target Group	(1) Short-run R&D Stimulus, $m	(2) Additional R&D Dynamics and Spillovers, $m	(3) Total R&D Increase (columns 1+2), $m	(4) Total Output Increase, $m
1. All Firms	870	755	1,625	6,178
2. US R&D Tax Credit (firms eligible in median year)	870	779	1,650	5,982
3. Smaller Firms (smallest 50%)	870	513	1,384	3,745
4. Larger Firms (largest 50%)	870	765	1,636	6,287

Panel B

Target Group	(1) % firms	(2) Average SIC	(3) Average TECH
1. All Firms	100	0.046	0.127
2. US R&D Tax Credit (firms eligible in median year)	40	0.052	0.131
3. Smaller Firms (smallest 50%)	50	0.041	0.074
4. Larger Firms (largest 50%)	50	0.047	0.129

Notes: All numbers in 1996 prices and simulated across all firms who reported non-zero R&D at least once over the 1990-2001 period. We use our "preferred" systems of equations as in Table 8 Details of calculations are in Appendix E. In Panel A we consider four different experiments. The first row gives every firm 1% extra R&D. Given average R&D spending in the sample this "costs" $870m in the short-run (column (1)). We predict (column (2)) that incorporating dynamics and spillovers this will generate an extra $755m of R&D giving a total of total of $1,625m in column (3). This is associated with an extra $6,178m increase in production (column 4) in the long-run).

The other rows consider a stimulus of the same aggregate size ($870m) but distributed in different ways (column (1) of Panel B gives the proportion of firms affected). Row 2 is calibrated to a stylized version of the current US R&D tax credit (see text for details) and assumes all eligible firms (40% under our stylized scheme) increase R&D by the same proportionate amount (capping the total at $870m). Row 3 considers an experiment that gives an equi-proportionate increase in R&D to the smallest 50% of firms (by mean 1990s employment size). Row 4 does the same for the largest 50% of firms.

In Panel B, the SIC and TECH average values have been calculated after weighting by the R&D of the spillover receiving firm times the R&D of the spillover generating firm. This accounts for the average closeness of difference groups of firms and also the absolute size of the spillovers.

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.