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Identifying technology spillovers and product market rivalry

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Identifying technology spillovers and product market rivalry*

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Abstract

Support for many R&D and technology policies relies on empirical evidence that R&D "spills over" between firms. But there are two countervailing R&D spillovers: positive effects from technology spillovers and negative effects from business stealing 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 exploit these using distinct measures of a firm's position in *technology* space and *product market* space. We show using panel data on U.S. firms between 1981 and 2001 that both technology and product market spillovers operate, but that net social returns are several times larger than private returns. The spillover effects are also revealed when we analyze three high-tech sectors in detail - pharmaceuticals, computer hardware and telecommunication equipment. Using the model we evaluate three R&D subsidy policies and show that the typical focus of support for small and medium firms may be misplaced.

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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 strategic interaction among firms and long run growth[1], and while many empirical studies appear to support the presence of technological 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 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, Romer (1991), Aghion and Howitt (1992), Spence (1984), and Reinganum (1989); and Griliches (1992) and Keller (2004) for 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]. The significant variation in these two dimensions allows us to distinguish between technology and rivalry 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, but the social returns from R&D are still positive and the former dominates the latter. To a first approximation the social returns to R&D are about 3.5 times the private returns. We also find that R&D by product market rivals is a strategic complement for a firm's own R&D. Using parameter estimates from the model we evaluate the aggregate productivity effects of three different R&D subsidy policies and show that the typical focus of R&D support

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

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

for medium and small firms may be misplaced.

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 own 'inside' R&D in a production, cost or innovation function. The simplest version is to measure the spillover pool as the stock of knowledge generated by other firms in the industry (e.g. Bernstein and Nadiri, 1989). This assumes that firms only benefit from R&D by other firms in their industry, and that all such firms are weighted equally in the construction of the spillover pool. Unfortunately, This makes identification of the strategic rivalry effect of R&D from technological 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 available to firm i as $G_i = \Sigma_{j,j\neq i} w_{ij} G_j$ where w_{ij} is some 'knowledge-weighting matrix' applied to the R&D stocks (Gj) 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}, and there are many approaches to constructing the knowledge-weighting matrix. Best practice is probably the method first used by Jaffe (1986), exploiting firm-level data on patenting (or R&D spending) 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 from multiproduct firms to construct an analogous distance measure in product market space[5].

[4]The same is true for papers that use "distance to the frontier" as a proxy for the potential size of the technological spillover. In these models the frontier is the same for all firms in a given industry (e.g. Acemoglu, Aghion and Ziblotti, 2003).

[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.

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" (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 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 lagged variables and 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 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.

[6] As Griliches (1979) points 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.

2. Analytical Framework

We consider the empirical implications of a non-tournament model of R&D with technological spillovers and strategic interaction in the product market[7]. In Appendix A we analyze a tournament model of R&D with an identical product market structure to the one analyzed here, and find the qualitative predictions are similar.

We study a two-stage game. In stage 1 firms decide their R&D spending and this produces knowledge (patents) that are 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 in the product market. 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.

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

[7] This approach has some similarities to Jones and 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.

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 benefitting from spillovers from firms that it is close to in technology space: $k_0 = \phi(r_0, r_\tau)$ where we assume that the knowledge production function ϕ is non-decreasing and concave in both arguments. This means that if there are knowledge spillovers, they are necessarily positive. We assume that the function ϕ is common to all firms.

Firm 0 solves the following problem:

$$\max_{r_0} V^0 = \Pi(\phi(r_0, r_\tau), k_m) - r_0. \tag{2.1}$$

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 argu-

[8]We assume that innovation by firm m affects firm $0's$ profits only through x_m, which is plausible in most contexts.

[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.

ments.[10] By comparative statics,

$$\frac{\partial r_0^*}{\partial r_\tau} = -\frac{\{\Pi_1 \phi_{1\tau} + \Pi_{11}\phi_1\phi_\tau\}}{A} \tag{2.2}$$

where $A = \Pi_{11}\phi_1 + \Pi_1\phi_{11} < 0$ 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 of $\frac{\partial r_0^*}{\partial r_\tau}$ is formally ambiguous.

Comparative statics also yield

$$\frac{\partial r_0^*}{\partial r_m} = -\frac{\Pi_{12}\phi_1}{A} \tag{2.3}$$

Thus firm $0's$ R&D is an increasing (respectively decreasing) function of the R&D done by firms in the same product market if $\Pi_{12} > 0$ – i.e., if k_0 and k_m are strategic complements (respectively substitutes).[11]

We also get obtain[12]

$$\frac{\partial k_0}{\partial r_\tau} = \phi_2 > 0 \quad \text{and} \quad \frac{\partial k_0}{\partial r_m} = 0 \tag{2.4}$$

[10] If we allowed for firms in τ and m to overlap, there would be an additional term reflecting the fact that the R&D spillover to firm τ also affects k_m and thus has a negative strategic effect on its own profits.

[11] It is worth noting that most models of patent races embed the assumption of strategic complementarity because the outcome of the race depends on the gap in R&D spending by competing firms. This observation applies both to single race models (e.g., Loury, 1979; Lee and Wilde, 1980; Reinganum, 1982) and more recent models of sequential races (Aghion, Harris and Vickers, 1997; and Aghion et al, 2005). 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.

[12] One qualification should be noted. Strictly speaking, the result $\frac{\partial k_0}{\partial r_m} = 0$ holds if k measures the stock of knowledge. But in practice we will measure k by using patenting information. If the patenting decision is based on the potential market value of the innovation,then we would expect $\frac{\partial k_0}{\partial r_m} < 0$, because the firm will choose to patent fewer inventions.

We summarize these results in Table 1

[Table 1 about here]

Two points about identification from the table should be noted. First, the empirical identification of strategic complementarity or substitution comes only from the R&D equation. Identification cannot be obtained from the patents (knowledge) or value equations because the predictions are the same for both forms of strategic rivalry. Second, the presence of spillovers can in principle be identified from the R&D, patents and value equations. Using multiple outcomes thus provides a stronger test than we would have from any single indicator.

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 data from the NBER data archive. This contains detailed information on almost 3 million U.S. patents granted between January 1963 and December 1999 and all citations made to these patents between 1975 and 1999 (over 16 million)[13]. 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 36 year period were dropped), leaving an unbalanced panel of 736 firms with at least four observations between 1980 and 2001. Appendix B provides details on all datasets.

3.1. Calculating Product Market Closeness

Our measure of product market closeness uses Compustat data on the sales and 4-digit SIC codes of the major line of business by firm from 1993 onwards. On

[13]See Hall, Jaffe and Trajtenberg (2001).We also constructed a cite weighted firm patent count as a quality adjusted measure of the raw patent count.

average each firm reports 4.7 different lines of business covering 5.4 different 4-digit SIC codes, spanning 597 industries across the sample. We use average share of sales per SIC code within each firm over the period as our measure of activity by product market, $S_i = (S_{i,1}, S_{i,2}, ...S_{i,597})$, where $S_{i,j}$ is the share of sales of firm i in the 4-digit SIC code j.[14] The product market closeness measure, $SIC_{i,j}$ $(i \neq j)$, is then calculated as the uncentered correlation between all firms pairings following Jaffe (1986):

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

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

$$SPILLSIC_{it} = \Sigma_{j,j \neq i} SIC_{ij} G_{jt} \tag{3.1}$$

where G_{jt} is the stock of R&D by firm j in year t.

3.2. Patent Data and 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 activity by technology market, $T_i = (T_{i,1}, T_{i,2}, ...T_{i,426})$, where $T_{i,j}$ is the share of patents of firm i in technology class j. The technological closeness measure, $TECH_{i,j}$ $(i \neq j)$, is also calculated as the uncentered

[14] The breakdown by SIC 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 timings of the patent technology distance measure to demonstrate robustness to the exact timing (see below).

correlation between all firms pairings:

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

This ranges between zero and one, depending on the degree of technology market overlap[15] We construct the pool of technological spillover R&D for firm i in year t, $SPILLTECH_{it}$,as

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

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 about 18,000), but with heterogeneity in size, R&D intensity, patenting activity and market valuation. The two closeness measures also differ widely across firms[16].

[Table 2 about here]

3.3. Identification of Product Market versus Technology Distance

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 0.47, suggesting these do reflect some differential characteristics of firms. After weighting with R&D stocks following equations (3.2) and (3.1) the correlation between

[15] We pooled across the entire sample period and also experiemented with sub-samples. Using 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 and (since firms only shift technology area slowly). The larger sample enabled us to pin down the firm's position more accurately.

[16] The absolute level of these measures will, of course, depend on the degree of aggregation of the underlying patent and product market classes.

$SPILLTECH$ and $SPILLSIC$ is 0.42, and for estimation with fixed effects the relevant correlation in the change of $SPILLTECH$ and $SPILLSIC$ is only 0.17. Second we plot SIC against TEC in Figure 1 from which it is apparent that the positive correlation we observe is caused by a dispersion across the unit box rather than a few outliers. Finally, in Appendix C 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.

4. Econometrics

4.1. Generic Issues

There are three main equations of interest that we wish to estimate: a market value equation, an R&D equation, and a patents equation[17]. 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 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

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

below.[18] 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[19]. 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[20]. Third, the model in (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 Griliches (1981)[21]

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

where V is the market value of the firm, A is the stock of tangible assets, G is the stock of R&D, and the superscript v indicates that the parameter is for the market value equation. The deviation of V/A (also known as "Tobin's average Q") from unity depends on the ratio of the R&D stock to the tangible capital stock (G/A) and κ_{it}. We parameterize this as

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

[18] We have between 4 and 21 years of continuous firm observations in our sample. In the R&D equation, for example, the mean number of observations is 18.

[19] 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.

[20] 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) to explicitly use the lags as instruments - we report some experiments using these GMM based approaches in the results section.

[21] See also Jaffe (1986), Hall et al (2000) or Lanjouw and Schankerman (2004).

where η_i^v is the firm fixed effect, τ_t^v 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. R&D equation

We write the R&D equation as:

$$\ln R_{it}=\alpha^r\ln R_{it-1}+\beta_1^r\ln SPILLTECH_{it-1}+\beta_2^r\ln SPILLSIC_{it-1}+Z_{it}^{r\prime}\beta_3^r+\eta_i^r+\tau_t^r+\upsilon_{it}^r \qquad (4.4)$$

The main issue to note is that the contemporaneous value of $SPILLTECH$ and $SPILLSIC$ would be particularly difficult to interpret in equation (4.4) 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 (4.4). Our (admittedly partial) defence against this problem are that we lag the independent variables by a year and we include a variety of controls to account for the other factors driving this correlation (such as a distributed lag in industry sales).

4.4. 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[22]

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

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:

$$\begin{aligned} E(P_{it}|X_{it}, P_{it-1}) &= \exp\{\delta_1 D_{it} \ln P_{it-1} + \delta_2 D_{it} + \beta_1^p \ln SPILLTECH_{it-1} + \\ &\quad \beta_2^p \ln SPILLSIC_{it-1} + Z_{it}^{p\prime}\beta_3^p + \eta_i^p + \tau_t^p\} \end{aligned} \tag{4.5}$$

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 "overdispersion", relaxing the Poisson restriction that the mean equals the variance ($\alpha = 0$).

We introduce firm fixed effects into the count data model using the "mean scaling" method of Blundell, Griffith and Van Reenen (1999). This relaxes the strict exogeneity assumption underlying Hausman, Hall and Griliches (1984). Essentially, we exploit the fact that we have a long pre-sample history (of up to 15 years per firm) on patenting behaviour to construct its pre-sample average. This can then be used as an initial condition to proxy for unobserved heterogeneity if the first moments of the variables are stationary. Although there will be some

[22] See Blundell, Griffith and Van Reenen (1999) and Hausman, Hall and Griliches (1984) for discussions of count data models of innovation.

finite sample bias Monte Carlo evidence shows that this pre-sample mean scaling estimator performs well compared to alternative econometric estimators for dynamic panel data models with weakly endogenous variables (see Blundell, Griffith and Windmeijer (2002)).

4.5. Production Function

Although the production function is implicit in theoretical structure outlined above it is useful for evaluating the impact of policies on social returns to R&D. Although we consider more complex forms, the basic production function is of the R&D augmented Cobb-Douglas form:

$$\ln Y_{it} = \beta_1^y \ln SPILLTECH_{it-1} + \beta_2^y \ln SPILLSIC_{it-1} + Z_{it}^{y\prime}\beta_3^y + \eta_i^y + \tau_t^y + \upsilon_{it}^y \quad (4.6)$$

where Y is real sales. 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 (4.6) would be the same as that in the patent equation (i.e. $\beta_1^y > 0$ and $\beta_2^y = 0$). 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 (4.6) are the same as those of the market value equation. Controlling for industry sales dynamics (see Klette and 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.

5. Empirical Results

[Tables 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. As noted in Section 4, we use a series expansion in the own R&D stock to tangible capital stock ratio to capture the nonlinearity in the value equation because it is easier to incorporate fixed effects in this specification. The coefficients of the other variables in column (1) were close to those obtained from nonlinear least squares estimation[23]. In this specification without any firm fixed effects, the product market spillover variable, $SPILLSIC$, has a positive impact on market value of the firm and $SPILLTECH$ is insignificant. 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.

Recall that we include a sixth-order series of the 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 0.241 (at the mean). A ten percent

[23] For example, using non-linear least squares (NLLS), the coefficients (standard errors) on $SPILLTECH$ and $SPILLSIC$ were -0.036 (0.008) and 0.039 (0.004), respectively (compared to -0.040 (0.012) and 0.038 (0.007) in OLS). Using OLS and just the first order term of G/A, the coefficient (standard errors) on G/A was 0.284 (0.011), as compared to 0.826 (0.037) under NLLS. 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).

increase in the stock of R&D for the firm is associated with an increases in its market value of about 2.4 percent. Evaluated at the sample means, this implies that an extra dollar of R&D is worth about \$1.18 in market value. This represents the return net of the cost of the R&D, of course (if the private returns just covered the cost of the R&D, market value would not increase). This estimate is higher than the 86 cent figure obtained by Hall, Jaffe and Trajtenberg (2001) over an earlier sample period[24].

When we allow for fixed effects, the estimated coefficient on $SPILLTECH$ switches signs and becomes positive and significant as compared to column (1)[25]. 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 by 4.32 cents. That is if another firm with perfect overlap in technology areas ($TEC = 1$) raised its R&D by one dollar the firms market value would rise by 4.32 cents. Comparing this figure to the return from own-R&D (\$1.18), 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 $SPILLSIC$ generates a 0.67 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 4.36 cents. Interestingly, the negative impact of an extra dollar of product market rivals' R&D is very similar in magnitude to the positive impact of a dollar of technology (R&D) spillovers. Of course, the net effect of

[24] If we re-estimate over the sample period in Hall et al (2000) we find a similar average private return to the one they obtain.

[25] 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).

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 should depress 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 the technology spillover variable is 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 technological 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 these correlated effects[26].

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[27]. $SPILLTECH$ has a positive and highly significant association with patenting, indicating the presence of technological 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

[26] 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 0.281 (*0.091*) and on $SPILLSIC$ of -0.075 (*0.029*).

[27] We also tried weighting the patent counts by future citations, but this made little difference to the main results. We do, however, report these in experiments for specific high tech industries below.

of sales to capture demand factors. At sample means, our estimate implies that an increase in own-R&D stock of one dollar would generate 0.007 extra patents – equivalently, the cost of the marginal patent produced by own R&D is about $133,000. Turning to our key variables, allowing for fixed effects reduces the coefficient on $SPILLTECH$, but it remains positive and significant at the 5% level. Evaluated at the sample means, the estimates for $SPILLTECH$ imply that an extra dollar of technology spillovers generates 0.00022 extra patents. Comparing this figure to the figure for own-R&D, we conclude that a dollar of technology spillovers is only worth 3 percent as much to a firm as a dollar of its own R&D (in terms of extra patents generated). Note, that our qualitative findings do not depend on the precise distributional assumptions underlying the Negative Binomial model. Using a GMM estimator that relies only on the first moment condition leads to similar results[28].

Finally, in column (3) we present our preferred specification, which includes both firm fixed effects and lagged patent counts[29]. Not surprisingly, we find strong persistence in patenting (the coefficient on lagged patents is highly significant). In this model $SPILLSIC$ is insignificant at conventional levels whereas $SPILLTECH$ retains a large and significant coefficient.

To summarize, patents are a knowledge output and should be affected by technological spillovers but not strategic rivalry (at least in our simple models). The empirical results are consistent with these predictions.

[28] For example, we used the specification model in column (2) but instrumented firm R&D and firm sales with their own lagged values dated $t-2$ to $t-4$. $SPILLTECH$ had a positive and significant coefficient (0.698 with a standard error of 0.333) and $SPILLSIC$ had an insignificant coefficient (0.023 with a standard error of 0.089).

[29] The pre-sample estimator assumes we can capture all of the fixed effect bias by the long pre-sample history of patents (up to 15 years). 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 10 years of continuous time series data. Only the pre-sample sales variable was significant at 5% and this did not change any of the main results.

5.3. R&D Equation

We now turn to the coefficient estimates for the R&D equation (Table 5). In the static specification without firm fixed effects (column (1)), we find that both technology and product market spillovers are present[30]. The positive coefficient on $SPILLSIC$ indicates that own and product market rivals' R&D (knowledge stocks) 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. We also find that the coefficient on lagged firm sales is large (elasticity of 0.80) and highly significant. When we include firm fixed effects (column (2)), the coefficient on $SPILLSIC$ declines substantially (to a third of its earlier value) but remains positive and highly significant, again indicating strategic complementarity. The coefficient on $SPILLTECH$ also falls sharply and becomes insignificant. When we include dynamics (lagged R&D) $SPILLSIC$ is still significant at the 10% level and the implied, long run effect are slightly lower than the static specification (0.082). Dropping the insignificant $SPILLTECH$ in column (4) improves the precision on $SPILLSIC$ which is now significant at conventional levels[31].

To summarize, we find evidence that R&D spending by a firm and its *product market rivals* are strategic complements, even after we controlling for industry

[30] The fixed effects are highly significant (p-value under .001). A Hausman Test of random effects with three digit industry dummies is rejected in favour of fixed effects (p-value=0.022).

[31] We checked that the results were robust to allowing sales and lagged R&D to be endogenous by re-estimating the R&D equation using the Blundell and Bond (1998) GMM "system" estimator. The qualitative results were the same. We used lagged instruments dated t-2 to t-8 in the differenced equation and lagged differences dated t-1 in the levels equations. In the most general dynamic specification of column (3) the coefficient (*standard error*) on $SPILLSIC$ was 0.096(*0.017*) and the coefficient (*standard error*) on $SPILLTECH$ was -0.024 (*0.020*). Since the lagged dependent variable took a coeffiicent of 0.819(0.032), however, this implies a *larger* magnitude of the effect of $SPILLSIC$ on R&D than the main OLS specifications. The instruments were valid at the 5% level.

level demand and firm fixed effects[32].

5.4. Production Function

Table 6 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 a positive and significant coefficient on $SPILLSIC$ and a negative sign on the technological spillover term, $SPILLTECH$. 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 qualitatively the same as the marginal effects of spillovers on innovative output (as measured by patents). The third column drops the insignificant $SPILLSIC$ term and is our preferred specification.

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[33]. We also experimented with using a proxy for value added instead of real sales as the dependent variable (following the same procedure as Bresnahan et al. (2002) - see Appendix B for details). This led to a similar pattern of results[34].

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

[33] $SPILLTECH$ took a coefficient of 0.089 and a standard error of 0.045 and $SPILLSIC$ remained insignificant (coefficient of 0.015 and a standard error of 0.123). Including a full set of two digit industry time trends also lead to the same findings. The coefficient (*standard error*) on $SPILLTECH$ was 0.085 (0.047).

[34] When using value added as the dependent variable the coefficient (*standard error*) on $SPILLTECH$ was 0.189(*0.053*) and on $SPILLSIC$ was -0.016(*0.012*). Including materials on

[Tables 7, 8, 9 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 3-5. The match between the theoretical predictions and the empirical results is quite close. 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 of equations in the model (see Appendix D) 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. 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 9.8 percent, so that the 1% stimulus generates 1.098% more R&D. The amplification

the right hand side generated a coefficient (*standard error*) on $SPILLTECH$ of 0.127(*0.038*) and on $SPILLSIC$ of -0.005(*0.009*).

effects on patents, market value and productivity are all much larger. The amplification effect for patents is more than twice as large as the autarky effect (0.502 versus 0.231). Since we found that the coefficient on $SPILLSIC$ in the preferred specification of the patent equation was not significant, the amplification is coming from technology spillovers and strategic complementarity in R&D. The amplification effect on market value is about one-third the direct effect (0.270 versus 0.728). Finally, the amplification effect of spillovers on productivity is particularly large - about two and a half times the size of the direct 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. 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. This confirms the conventional wisdom of under-investment in private R&D, and thus a role for policy support for R&D.

5.6. 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 - Pharmaceuticals, Computer Hardware and Telecommunications Equipment. The results from these experiments are summarized in Table 9.

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 (especially when we weight by patent citations[35]). Consistent with the theory there is no evidence of $SPILLSIC$ in the patents equation or in the production function. There is some indication of strategic complementarity in the R&D equation, as the $SPILLSIC$ term is positive; however it is not statistically significant. 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 spillover terms are all insignificant in the R&D equation. The results are slightly different in the Telecommunications Equipment industry. Although we *do* observe significant technology spillover effects in the market value equation, the production function and cite-weighted patents equations, we do *not* observe any evidence of significant product market rivalry (i.e. the $SPILLSIC$ term is negative but small and insignificant in the value equation)[37].

[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.

[37] We also calculated "rates of return to R&D" (own and spillovers) calculated at the industry specific sample means. The return to a dollar of own R&D was reasonably similar to the overall sample (\$1.18) in Computers (\$0.77) and Telecoms (\$1.23). It was much higher in Pharmaceuticals (\$3.65) - a result also found in Lanjouw and Schankerman (2004). The return to a dollar of $SPILLTECH$ is higher in each of the three high-tech industries (\$0.247, \$0.864 and \$0.144 in Pharmaceuticals, Computers and Telecom respectively), as compared to the return in the sample as a whole (\$0.043). The rivalry effect of a dollar of $SPILLSIC$ is stronger in Pharmaceuticals (-\$0.82) and Computers (-\$0.236) than in the overall sample (-\$0.044). It is lower in Telecoms (-\$0.008).

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, possibly due to the smaller sample size. We leave for future research a more detailed analysis of particular industries using our approach.

[Table 10 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 10). 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 effects in the model this generates an extra $95.0 million of R&D (for a total R&D increase of $965.0 million). This is associated with an extra $2,717 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)[38]. 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 10).

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 SMEs (small and medium sized enterprise).[39] 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 $2.8 billion of extra output, as compared to only $1.6 billion 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 of TEC for large firms is 0.130 as compared to 0.074 for "smaller" firms[40]. That

[38] 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 Bloom et al, 2002 for a detailed analysis of R&D policies). 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.

[39] 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).

[40] 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

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 1981 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. 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.

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 Pinkse et al

dummy with $SPILLTECH$ in the production function (Table 6, column 2). This interaction was negative, as expected, but insignificant (coefficient of -0.019 with a standard error of 0.026).

(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.

References

Acemoglu, Daron, Philippe Aghion, and Fabrizzio Ziblotti (2003) "Distance to Frontier, Selection and Economic Growth", mimeo MIT.

Aghion, Philippe and Peter Howitt (1992) "A model of growth through creative destruction" *Econometrica*, 60:323-51

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith and Peter Howitt (2005) "Competition and Innovation: An Inverted U Relationship?" forthcomming in *Quarterly Journal of Economics*

Austin, David (1993), "An Event Study approach to measuring innovative output: The case of Biotehcnology"*American Economic Review,* 83, 2: 235-258

Bartelsman, Erik, Randy Becker and Wayne Gray (2000) NBER Productivity Database, available at www.nber.org

Bernstein, Jeffrey and M. Ishak Nadiri (1989), "Research and Development and Intra-industry Spillovers: An Empirical Application of Dynamic Duality", *Review of Economic Studies* 56, 249-269

Bloom, Nick, Rachel Griffith and John Van Reenen (2002), "Do R&D Tax Credits Work?" *Journal of Public Economics* 85 1-31

Blundell, Richard and Stephen Bond (1998) "Initial Conditions and moment restrictions in dynamic panel data models" *Journal of Econometrics*, 87: 115-143

Blundell, Richard, Rachel Griffith and John Van Reenen (1999) "Market Shares, Market Value and Innovation in a Panel of British Manufacturing Firms" *Review of Economic Studies*, 66, 529-554

Blundell, Richard, Rachel Griffith and Frank Windmeijer (2002) "Individual Effects and Dynamic Feedback in Count Data Models" *Journal of Econometrics*, 108, 113-131

Branstetter, Lee and Mariko Sakakibara (2002) "When do research consortia work well and why? Evidence from Japanese panel data" *American Economic Review,* 92,1, 143-159

Breshnahan, Timothy, Erik Brynjolfsson and Lorin Hitt (2002), "Information technology, workplace organisation, and the demand for skilled labor: firm-level evidence", *Quarterly Journal of Economics*, CXVII, 339-376.

Cockburn, Iain and Rebecca Henderson (1994), "Racing To Invest? The Dynamics of Competition in Ethical Drug Discovery," *Journal of Economics and Management Strategy,* 3(3), 481-519.

Griliches, Zvi (1981), "Market Value, R&D and Patents" *Economics Letters*, 7, 183-187

Griliches, Zvi (1992), "The Search for R&D Spillovers", *Scandinavian Journal of Economics* 94, supplement, S29-S47

Griliches, Zvi (1998), *R&D and Productivity: The Econometric Evidence* (Chicago: University of Chicago Press)

Griliches, Zvi, Hall, Bronwyn. and Pakes, Ariel (1991) "R&D, patents and market value revisited: Is there a Second (technological opportunity) frontier?" *Economics of Innovation and New Technology*, 1, 183-201

Hall, Bronwyn, Jaffe, Adam and Trajtenberg, Manuel (2001), "Market Value and Patent Citations: A First Look," NBER Working Paper No. 6507 (forthcoming in *RAND Journal of Economics,* 2005)

Hausman, Jerry, Hall, Bronwyn and Griliches, Zvi (1984) "Econometric Models for Count Data and an Application to the Patents-R&D Relationship" *Econometrica*, 52, 909-938

Jaffe, Adam (1986), "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value", *American Economic Review* 76, 984-1001

Jaffe, Adam(1988), "Demand and Supply Influences in R&D Intensity and Productivity Growth," *Review of Economics and Statistics,* 70 (3), 431-437.

Jaffe, Adam, Manuel Trajtenberg and Rebecca Henderson (1993), "Geographic Localisation of Knowledge Spillovers as Evidenced by Patent Citations", *Quarterly Journal of Economics* 108 (3), 577-598

Jones, Chad and John Williams (1998) "Measuring the Social Rate of Return to R&D", *Quarterly Journal of Economics*, 113(4), 119-35.

Keller, Wolfgang (2004), "International Technology Diffusion", forthcoming, *Journal of Economic Literature*

Klette, Tor and Zvi Griliches (1996), "The Inconsistency of Common Scale Estimators when Output Prices are Unobserved and Endogenous," *Journal of Applied Econometrics*, 11, 343-361

Lanjouw, Jenny and Mark Schankerman (2004), "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators," *Economic Journal,* 114 (April), 441-465.

Lee, Tom and Louis Wilde (1980) "Market Structure and Innovation: A Reformulation" *Quarterly Journal of Economics*, 94: 431-436

Lerner, Josh (1997), "An Empirical Exploration of a Technology Race" *RAND Journal of Economics*, 28(2), 228-247

Loury, Glenn (1979) "Market Structure and Innovation" *Quarterly Journal of Economics*, 93: 395-410

Manski, Charles (1991), "Identification of Endogenous Social Effects: The Reflection Problem", *Review of Economic Studies* 60 (3), 531-42

Megna, Pamela and Mark Klock (1993), "The Impact of Intangible capital on Tobin's q in the Semiconductor Industry"" *American Economic Review*, 83, 2, 265-269

Nickell, Stephen (1981), "Biases in Dynamics Models with Fixed Effects, *Econometrica,* 49, 1417-1426.

Pinkse, J., Margaret Slade and C. Brett (2002), "Spatial Price Competition: A Semi-Parametric Approach," *Econometrica,* 70, 1111-1155.

Reinganum, Janet (1989) "The timing of Innovation: Research, Development and Diffusion" in R. Schmalensee and R.D. Willig eds, *Handbook of Industrial Organization*, vol 1., New York: North Holland

Spence, Michael (1984), "Cost Reduction, Competition and Industry Performance", *Econometrica* 52, 101-121

Tirole, Jean (1994), *The Theory of Industrial Organization* (Cambridge, MIT Press).

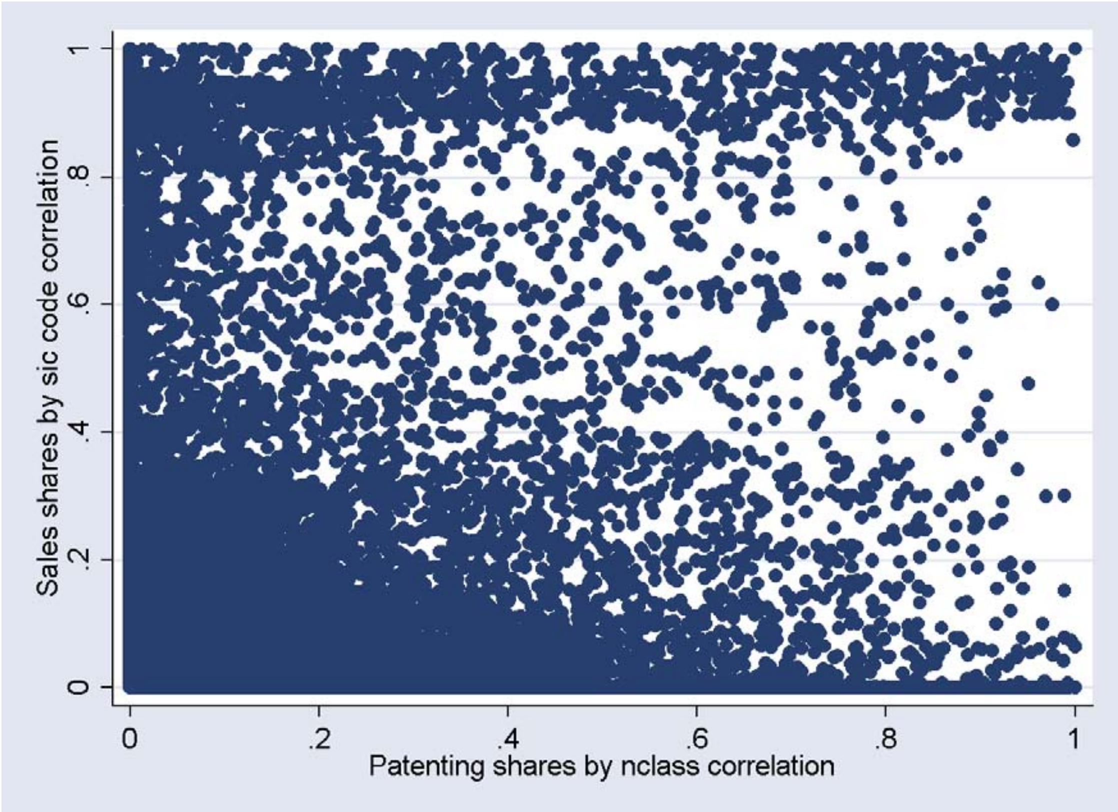

FIGURE 1 –
SIC AND TEC CORRELATIONS

Notes: This figure plots the pairwise values of SIC (closeness in product market space between two firms) and TEC (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

Comparative static prediction	Empirical counterpart	No Technological Spillovers Strategic complements	No Technological Spillovers Strategic Substitutes	Some Technological Spillovers Strategic complements	Some Technological Spillovers Strategic Substitutes
$\partial V_0/\partial r_\tau$	Market value with SPILLTECH	Zero	Zero	Positive	Positive
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	Negative	Negative	Negative
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Zero	Zero	Positive	Positive
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	Zero	Zero	Zero
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Zero	Zero	Ambiguous	Ambiguous
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Positive	Negative	Positive	Negative

Notes: See text for full derivation of these comparative static predictions

TABLE 2 -
DESCRIPTIVE STATISTICS

variable	Mnemonic	Mean	Median	Standard deviation
Tobin's Q	V/A	2.33	1.39	2.96
Market Value, $m	V	3,929	424	15,841
R&D Stock, $m	G	605	28	2,723
R&D stock/fixed capital	G/A	0.47	0.17	0.94
R&D flow, $m	R	90	3	434
Technological spillovers, $m	SPILLTECH	21,873	17,390	17,622
Product market rivalry, $m	SPILLSIC	6,069	1,912	9,498
Patent flow, #	P	16	1	74
Sales, $m	Y	3,133	494	9,741
Fixed capital, $m	A	1,182	103	4,111

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

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 SPILLTEC)
Ln($SPILLTECH_{t-1}$)	-0.040	0.240	0.186	
	(0.012)	(0.104)	(0.100)	
Ln($SPILLSIC_{t-1}$)	0.038	-0.067		-0.047
	(0.007)	(0.031)		(0.031)
Ln(Industry $Sales_t$)	0.434	0.294	0.298	0.299
	(0.068)	(0.044)	(0.044)	(0.044)
Ln(Industry $Sales_{t-1}$)	-0.502	-0.170	-0.176	-0.164
	(0.067)	(0.045)	(0.045)	(0.043)
Polynomial terms in lagged (R&D Stock/Capital Stock)				
Ln(R&D Stock/Capital $Stock)_{t-1}$	0.898	0.801	0.792	0.800
	(0.154)	(0.197)	(0.198)	(0.199)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^2$	-0.218	-0.385	-0.374	-0.374
	(0.214)	(0.222)	(0.222)	(0.223)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^3$	-0.006	0.120	0.115	0.115
	(0.111)	(0.103)	(0.103)	(0.104)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^4$	-0.010	-0.029	-0.020	-0.020
	(0.025)	(0.022)	(0.022)	(0.022)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^5$	-0.001	-0.002	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^6$	0.005 [a]	-0.007[a]	-0.006[a]	-0.006 [a]
	(0.009)	(0.007)	(0.008)	(0.008)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	Yes
No. Observations	10,011	10,011	10,011	10,011

[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	(4) Initial Conditions: Dynamics
$Ln(SPILLTECH)_{t-1}$	0.403	0.295	0.192	0.194
	(0.086)	(0.066)	(0.037)	(0.037)
$Ln(SPILLSIC)_{t-1}$	0.044	0.049	0.024	
	(0.032)	(0.031)	(0.019)	
$Ln(R\&D\ Stock)_{t-1}$	0.495	0.282	0.105	0.104
	(0.044)	(0.046)	(0.027)	(0.027)
$Ln(Sales)_{t-1}$	0.338	0.258	0.138	0.140
	(0.052)	(0.047)	(0.027)	(0.027)
$Ln(Patents)_{t-1}$			0.550	0.550
			(0.026)	(0.026)
Pre-sample fixed effect		0.450	0.175	0.174
		(0.049)	(0.028)	(0.028)
Over-dispersion (alpha)	0.954	0.814	0.402	0.402
	(0.067)	(0.046)	(0.029)	(0.029)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	Yes
4 digit industry dummies	Yes	Yes	Yes	Yes
No. Observations	9,122	9,122	9,122	9,122
Log Pseudo Likelihood	-20,559	-20,178	-18,697	-18,699

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 (columns (3) and (4)). The initial conditions effects in columns (3) and (4) are estimated through the "pre-sample mean scaling approach" of Blundell, Griffith and Van Reenen (1999) – see text.

TABLE 5 –
COEFFICIENT ESTIMATES FOR THE R&D EQUATION

Dependent variable: ln(R&D)	(1) No Effects	(2) Fixed Effects	(3) Fixed Effects + Dynamics	(4) Fixed Effects + Dynamics
Ln(SPILLTECH) $_{t-1}$	0.224	0.115	0.039	
	(0.017)	(0.071)	(0.039)	
Ln(SPILLSIC) $_{t-1}$	0.291	0.110	0.025	0.030
	(0.012)	(0.026)	(0.014)	(0.013)
Ln(Sales) $_{t-1}$	0.797	0.801	0.218	0.217
	(0.009)	(0.017)	(0.015)	(0.015)
Ln(R&D) $_{t-1}$			0.695	0.695
			(0.015)	(0.015)
Ln(Industry Sales) $_{t}$	0.698	0.133	0.133	0.134
	(0.083)	(0.030)	(0.022)	(0.022)
Ln(Industry Sales) $_{t-1}$	-0.879	-0.085	-0.110	-0.108
	(0.083)	(0.031)	(0.023)	(0.022)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	Yes
No. Observations	8565	8565	8395	8395
R^2	0.769	0.968	0.984	0.984

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 6 –
COEFFICIENT ESTIMATES FOR THE PRODUCTION FUNCTION

Dependent variable: Ln(Sales)	(1) No Fixed Effects	(2) Fixed effects	(3) Fixed effects
Ln(SPILLTECH) $_{t-1}$	-0.038	0.104	0.111
	(0.009)	(0.046)	(0.045)
Ln(SPILLSIC) $_{t-1}$	-0.008	0.009	
	(0.004)	(0.012)	
Ln(Capital) $_{t-1}$	0.291	0.164	0.165
	(0.009)	(0.012)	(0.012)
Ln(Labour) $_{t-1}$	0.646	0.628	0.627
	(0.012)	(0.015)	(0.015)
Ln(R&D Stock) $_{t-1}$	0.059	0.045	0.045
	(0.005)	(0.007)	(0.007)
Ln(Industry Sales) $_{t}$	0.208	0.197	0.198
	(0.040)	(0.021)	(0.021)
Ln(Industry Sales) $_{t-1}$	-0.105	-0.040	-0.040
	(0.040)	(0.022)	(0.022)
Year dummies	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes
No. Observations	10,092	10,092	10,092
R^2	0.945	0.989	0.989

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 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	0.240*	Yes
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	-0.067*	Yes
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Positive	0.192*	Yes
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	0.024	Yes
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Ambiguous	0.039	-
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Positive	0.025*	Yes

Notes: The theoretical predictions are for the case of technological spillovers with product market rivalry (strategic complements and non-tournament R&D) - this is the third column 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). A * denotes significance at the 10% level (note that coefficients are as they appear in the relevant tables, not marginal effects).

TABLE 8 –
AUTARKY, 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	0.098	1.098
				(0.053)	(0.053)
2	**Patents**	TECH, SIC and R&D	0.231	0.502	0.734
			(0.028)	(0.091)	(0.119)
3	**Market Value**	TECH, SIC and R&D	0.728	0.270	0.998
			(0.161)	(0.112)	(0.212)
4	**Productivity**	TECH, SIC and R&D	0.050	0.123	0.173
			(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 (4), Table 5 column (4) Table 6 column (3)). 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 –
ECONOMETRIC RESULTS FOR SPECIFIC HIGH TECH INDUSTRIES

A. Computer Hardware

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Tobin's Q	Patents	Cite-weighted patents	R&D	Real Sales
$\mathrm{Ln(SPILLTECH)}_{t-1}$	1.302	0.151	0.338	0.263	0.685
	(0.622)	(0.090)	(0.146)	(0.199)	(0.213)
$\mathrm{Ln(SPILLSIC)}_{t-1}$	-0.476	-0.005	0.157	0.039	-0.092
	(0.145)	(0.153)	(0.342)	(0.026)	(0.085)
Lagged dependent variable		0.717	0.427	0.684	
		(0.065)	(0.084)	(0.056)	
Observations	358	279	279	390	343

B. Pharmaceuticals

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Tobin's Q	Patents	Cite-weighted patents	R&D	Real Sales
$\mathrm{Ln(SPILLTECH)}_{t-1}$	1.628	-0.273	1.056	0.407	0.445
	(0.674)	(0.326)	(0.546)	(0.225)	(0.208)
$\mathrm{Ln(SPILLSIC)}_{t-1}$	-1.342	-0.106	-0.087	-0.395	-0.391
	(0.612)	(0.194)	(0.174)	(0.452)	(0.227)
Lagged dependent variable		0.218	0.269	0.590	
		(0.091)	(0.089)	(0.147)	
Observations	334	265	265	381	313

C. Telecommunication Equipment

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Tobin's Q	Patents	Cite-weighted patents	R&D	Real Sales
$\mathrm{Ln(SPILLTECH)}_{t-1}$	2.255	0.368	0.658	0.140	0.526
	(0.870)	(0.202)	(0.368)	(0.246)	(0.304)
$\mathrm{Ln(SPILLSIC)}_{t-1}$	-0.087	0.036	-0.010	0.033	0.147
	(0.446)	(0.110)	(0.217)	(0.118)	(0.156)
Lagged dependent variable				0.590	
				(0.063)	
Observations	405	353	353	429	390

Notes: 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 precious column but replaces all patent counts with their forward cite weighted equivalents; R&D (column (4)) corresponds to column (3) of Table 5; Sales (column 5) corresponds to column (2) of Table 6. Each Panel (A,B,C) are has results from separate industries (see Data Appendix)

TABLE 10 –
POLICY SIMULATIONS: SPILLOVER IMPACTS ACROSS DIFFERENT GROUPS OF FIRMS

Panel A

Target Group	(1) Total R&D Stimulus, $m	(2) Total R&D Spillovers, $m	(3) Total Productivity Spillovers, $m
1. All Firms	870	95.0	2,717
2. US R&D Tax Credit (firms eligible in median year)	870	94.9	2,747
3. Smaller Firms (smallest 50%)	870	91.2	1,581
4. Larger Firms (largest 50%)	870	95.1	2,767

Panel B

Target Group	(1) % firms	(2) Average SIC	(3) Average TEC
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	0.050	0.130

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. 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 (column (1)). We predict (column (2)) that incorporating dynamics and spillovers this will generate an extra $95.0m of R&D (a total $965.0m). This is associated with an extra $2,717m increase in production (column 3)).

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) to determine the eligible group (40% of firms) and assumes all eligible firms increase R&D by the same proportionate amount (capping the total at $870m). The final column again shows the impact on R&D and productivity. 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 TEC 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.

Appendices

A. Tournament Model of R&D Competition with Technological Spillovers

In this appendix 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

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

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.[1] 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 in the patent race is

$$(h_1F - 1)\{h^0 + (n-1)h^m + R\} - (h^0F - r_1)\{h_1^0 + (n-1)h_2^m\} = 0 \qquad \text{(A.2)}$$

Imposing symmetry and using comparative statics, we obtain

$$\begin{aligned} sign\left(\frac{\partial r_0}{\partial r_m}\right) &= sign\{h_{12}(hF(n-1) + rF - R\} + \{h_1(n-1)(h_1F - 1)\} \\ &\quad -\{h_{22}(n-1)(hF - R)\} - h_2\{(n-1)h_2F - 1\}\} \qquad \text{(A.3)} \end{aligned}$$

We assume $h_{12} \geq 0$ (spillovers do not reduce the marginal product of a firm's R&D) and $h_1F - 1 \geq 0$ (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 $(n-1)h_2F - 1 \leq 0$. 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.[2].

[1]The probability that firm 1 gets the patent might be decreasing in r_m in the absence of spillovers (it is normally assumed to be independent). The spillover term in our formulation can be thought of as net of any such effect.

[2]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.

B. Data Appendix

The main firm level data sample is generated through the combination of several datasets

The Compustat North-America dataset providing full accounts data for over 25,000 US firms from 1980 to 2001. This provides information on the key accounting information of R&D, fixed assets, employment, sales, etc.

The Compustat line of business dataset which provides details of sales broken down by into four digit SIC codes for 10,500 U.S. firms between 1993 and 2001 (checked by Compustat staff for accuracy). Prior to 1993 this information was not published by Compustat which explains why previous researchers have not used it (Compustat merely gave a main four digit SIC classification). Some firms have a further sub-division of their multiple lines of business data into a "primary" four digit SIC and a "secondary" four digit SIC classification . When this is the case we assumed that 75% of the sales was in the primary SIC and 25% in the secondary SIC. The results appear robust to alternative ways of dividing sales between primary and secondary classifications (for example, assuming that 67% was in the primary and 33% in the secondary SIC).

The NBER USPTO patents database described providing detailed patenting and citation information for around 2,500 firms (as described in Hall, Jaffe and Trajtenberg (2001)).

We started by matching the Compustat accounting data to the USPTO data, and kept only patenting firms leaving a sample size of 1,865. These firms were then matched into the line of business data, keeping only the 795 firms with data on both patents and sales by line of business, although these need not be concurrent. For example, a firm which patented in 1985, 1988 and 1989, had line of business data from 1993 to 1997, and accounting data from 1980 to 1997 would be kept in our dataset for the period 1985 to 1997. 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 in a non-parametric way. We also removed firms with less than four consecutive years of data. This left a final estimating sample of 736 firms 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 1998. The panel is unbalanced as we keep new entrants and exiters in the sample.

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 (Hall et al, 2000). 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 expenditures we use average wages and benefits at the four-digit industry level (Bartelsman, Becker and Gray, 2000, until 1996 and then Census Average Production Worker Annual Payroll by 4-digit NAICS code) and multiply this by the firm's reported employment level. This constructed measure is highly correlated at the industry level with materials. 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.

For Tobin's Q firm value is the sum of the values of common stock, preferred stock, 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 set to 0.1 for values below 0.1 and at 20 for values above 20. See also Lanjouw and 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 4-digit SIC code and year, and weighted up to the firm level in our panel using each firms distribution of sales across 4-digit SIC codes.

Industry price deflators were taken from (Bartelsman, Becker and Gray, 2000, until 1996 and then the BEA 4-digit NAICS Shipment Price Deflators afterwards).

In Table 9 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. Case Studies

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. These firms are close to each other in technology space as revealed by their patenting. IBM, for example, has a TECH correlation of 0.8 with Intel, 0.6 with Apple and 0.5 with Motorola (the overall average TECH correlation in the whole sample is 0.13 - see Table 10). 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 0.32 (the overall average SIC correlation in the whole sample is 0.05 - see Table 10). They both produce 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 to 0.02) because the latter firms mainly produce semi-conductor chips not computer hardware. IBM is not really competing with Intel and Motorola for customers. The SIC correlation between Intel and Mototrola is, as expected, rather high (0.35) because they are both competitors in supplying chips.

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.

D. Policy Experiments

The general specification of the empirical model can be written

$$\begin{aligned}
\ln R_{it} &= \alpha_1 \ln R_{it-1} + \alpha_2 \ln \sum_{j\neq i} TECH_{ij} G_{j,t-1} + \alpha_3 \ln \sum_{j\neq i} SIC_{ij} G_{j,t-1} + \alpha_4 X_{1,it} \\
\ln P_{it} &= \beta_1 \ln P_{it-1} + \beta_2 \ln G_{it-1} + \beta_3 \ln \sum_{j\neq i} TECH_{ij} G_{j,t-1} \\
&\quad + \beta_4 \ln \sum_{j\neq i} SIC_{ij} G_{j,t-1} + \beta_5 X_{2it} \\
\ln(V/A)_{it} &= \gamma_1 \ln(G/A)_{it} + \gamma_2 \ln \sum_{j\neq i} TECH_{ij} G_{j,t-1} + \gamma_3 \ln \sum_{j\neq i} SIC_{ij} G_{j,t-1} + \gamma_4 X_{3,it} \\
\ln Y_{it} &= \varphi_1 \ln G_{it} + \varphi_2 \ln \sum_{j\neq i} TECH_{ij} G_{j,t-1} + \varphi_3 \ln \sum_{j\neq i} SIC_{ij} G_{j,t-1} + \varphi_4 X_{4,it}
\end{aligned}$$

where R is the flow of R&D expenditure flow, G is the R&D stock, P is patent flow, V/A is Tobin's Q, Y is output and X_1, X_2, X_3 and X_4 are vectors of control variables. 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, and so set $R_{it} = R_{it-1}$ 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

$$\begin{aligned}
\ln R_i &= \alpha_0 + \frac{\alpha_2}{1-\alpha_1} \ln \sum_{j\neq i} TECH_{ij} R_j + \frac{\alpha_3}{1-\alpha_1} \ln \sum_{j\neq i} SIC_{ij} R_j + \frac{\alpha_4}{1-\alpha_1} X_{1i} \\
\ln P_i &= \beta_0 + \frac{\beta_2}{1-\beta_1} \ln R_i + \frac{\beta_3}{1-\beta_1} \ln \sum_{j\neq i} TECH_{ij} R_j + \frac{\beta_4}{1-\beta_1} \ln \sum_{j\neq i} SIC_{ij} R_j + \frac{\beta_5}{1-\beta_1} X_{2i} \\
\ln(V/A)_i &= \gamma_0 + \gamma_1 \ln(R/A)_i + \gamma_2 \ln \sum_{j\neq i} TECH_{ij} R_j + \gamma_3 \ln \sum_{j\neq i} SIC_{ij} R_j + \gamma_4 X_{3i} \\
\ln Y_{it} &= \varphi_0 + \varphi_1 \ln R_i + \varphi_2 \ln \sum_{j\neq i} TECH_{ij} R_{j,t-1} + \varphi_3 \ln \sum_{j\neq i} SIC_{ij} R_{j,t-1} + \varphi_4 X_{4i}
\end{aligned}$$

where $\alpha_0 = -\frac{\alpha_2+\alpha 3}{(1-\alpha_1)}\ln(r+\delta)$, $\beta_0 = -\frac{\beta_2+\beta_3+\beta_4}{(1-\beta_1)}\ln(r+\delta)$, $\gamma_0 = -(\gamma_1+\gamma_2+\gamma_3)\ln(r+\delta)$, and $\varphi_0 = -(\varphi_1+\varphi_2+\varphi_3)\ln(r+\delta)$

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

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

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

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

$$\lambda_i = \alpha_0 + \frac{\alpha_2}{1-\alpha_1}a_i + \frac{\alpha_3}{1-\alpha_1}c_i \tag{D.1}$$

$$\theta_{ij} = \frac{\alpha_2}{1-\alpha_1}b_{ij} + \frac{\alpha_3}{1-\alpha_1}d_{ij} \tag{D.2}$$

Using these approximations, we can write the R&D equation as

$$\ln R_i = \lambda_i + \sum_{j\neq i}\theta_{ij}\ln R_j + \frac{\alpha_4}{1-\alpha_1}X_{1i}$$

Let $\lambda, \ln R$ and X_1 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

$$\begin{aligned} \ln R &= \Omega^{-1}\lambda + \frac{\alpha_4}{1-\alpha_1}\Omega^{-1}X_1 \\ &\Longrightarrow \\ d\ln R &= \Omega^{-1}\frac{\alpha_4}{1-\alpha_1}dX_1 \end{aligned}$$

where $\Omega = I - H$.

This enables us to evaluate the firm-level distributional and macro aggregate impact of introducing shocks to any sub-group of firms.

D.1. Amplification Effects

D.1.1. R&D equation

Using the restrictions $\sum_{j\neq i} b_{ij} = \sum_{j\neq i} d_{ij} = 1$, it can be shown that $\Omega \times i = (1 - \frac{\alpha_2+\alpha_3}{1-\alpha_1})\ \iota$ where ι is a column vector of ones. It follows that the macro R&D response to a unit stimulus to R&D of each firm ($\frac{\alpha_4}{1-\alpha_1}dX_1 = 1$) is

$$\Omega^{-1} \times \iota = \frac{1-\alpha_1}{1-\alpha_1-\alpha_2-\alpha_3} x\ \iota$$

In the absence of technology and product market spillovers, R&D would increase by one percent. Thus we define the amplification effect as $\frac{1-\alpha_1}{1-\alpha_1-\alpha_2-\alpha_3} - 1$.

D.1.2. Patents equation

Using the approximations above, the patents equation is (ignoring constants)[3]

$$\ln P_i = \frac{\beta_2}{1-\beta_1}\ln R_i + \sum_{j\neq i}\rho_{ij}\ln R_j + \frac{\beta_5}{1-\beta_1}X_{2i}$$

where $\rho_{ij} = \frac{\beta_3}{1-\beta_1}b_{ij} + \frac{\beta_4}{1-\beta_1}d_{ij}$. By similar reasoning, we define the NxN matrix

[3] 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.

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

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

$$d \ln P = \frac{\beta_2}{1-\beta_1} d \ln R + [W \times d \ln R]$$

Using the result from the R&D amplification effect $d \ln R = \frac{1-\alpha_1}{1-\alpha_1-\alpha_2-\alpha_3} \times \iota$, we get the macro response of patents to a unit stimulus to R&D of each firm

$$\begin{aligned} d \ln P &= \frac{1-\alpha_1}{1-\alpha_1-\alpha_2-\alpha_3} \left(\frac{\beta_2}{1-\beta_1} \times \iota \times \iota' + W\right) \times \iota \\ &= \frac{1-\alpha_1}{1-\alpha_1-\alpha_2-\alpha_3} \left(\frac{\beta_2+\beta_3+\beta_4}{1-\beta_1}\right) \times \iota \end{aligned}$$

Thus the amplification effect on patents equals $\frac{1-\alpha_1}{1-\alpha_1-\alpha_2-\alpha_3}(\frac{\beta_2+\beta_3+\beta_4}{1-\beta_1}) - \frac{\beta_2}{1-\beta_1}$.

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

The calculations are completely analogous. For brevity, we do not repeat the details here.

APPENDIX TABLES

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

	Correlation	*IBM*	*Apple*	*Motorola*	*Intel*
IBM	SIC	1	0.32	0.01	0.01
	TECH	***1***	***0.64***	***0.47***	***0.76***
Apple	SIC		1	0.02	0.01
	TECH		***1***	***0.17***	***0.47***
Motorola	SIC			1	0.35
	TECH			***1***	***0.46***
Intel	SIC				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) 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.