Identifying technological spillovers and product market rivalry: theory and evidence from a panel of U.S. firms*

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Abstract

Firm performance is affected in two ways by the R&D activity of other firms. Benefits accrue from technological spillovers, but R&D by product market rivals can have strategic business stealing effects. We propose a methodology for identifying these two effects, which is based on two features. First, we distinguish a firm's position in *technology* space and *product market* space. Second, we use multiple indicators of firm performance (market value, patents and R&D). Using a quite general framework, we develop the implications of technology and product market spillovers for these different indicators and apply the approach to a panel of U.S. firms for the period 1981-2001. We find evidence both for technological spillovers and product market rivalry, and that R&D by product market rivals is a strategic complement for a firm's own R&D. A Simulation of our model shows that the impact of these spillovers is quantitatively large (especially for technology). Preliminary evidence also suggests that R&D subsidies focused to medium sized firms appear less cost effective than those focused on larger firms.

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1. Introduction

Research and Development (R&D) generates at least two distinct types of "spillover" effects. The first is *technological spillovers*, which increase the R&D productivity of other firms which are operating in similar technological areas. The empirical literature on technological (or knowledge) spillovers is extensive. The second type of spillover is the *product market rivalry effect* of R&D. When a firm does R&D, it increases its stock of knowledge. For firms which compete in similar product markets, this increase in 'competitive' knowledge has both a direct (business stealing) effect on its rivals and a strategic effect that induces a change in optimal R&D investment by its rivals. Although a major area in theoretical research, the product market rivalry effect of R&D has remained largely unexplored in the empirical literature, in part because it is difficult to distinguish the two types of spillovers using data on R&D at the firm level.

It is important to identify the empirical impact of these two types of spillovers for at least three reasons. First, econometric estimates of technological spillovers in the literature may be contaminated by product market rivalry effects, and it is difficult to ascertain the direction and magnitude of potential biases without building a model that incorporated both types of spillovers. Second, estimates of the impact of product market rivalry are needed to make an overall assessment of R&D spillovers for policy purposes. If product market rivalry effects dominate technological spillovers, the conventional wisdom that there is under-investment in R&D could be overturned. Third, such estimates would help in predicting the net effect on a firm of its rivals' R&D spending, which could be useful in formulating business strategy.

This paper develops an original methodology for identifying the separate effects of technological and product market spillovers and implements the method on a large sample of US firms. Our approach to identifying the effects of technological and product market spillovers is based on two features. First, we distinguish a firm's positions in *technology* space and *product market* space using information on the distribution of its patenting (across technological fields) and sales activity (across different industries). This allows us to construct separate measures of the distance between different firms in the technology and product market dimensions. Firms that are close in technology space will enjoy larger technological spillovers, while firms that are close in product market space will be exposed to stronger product market rivalry effects, other things equal. Provided we have sufficient variation in these two dimensions, it should be possible to distinguish between knowledge and rivalry spillovers.[1] The second feature of the approach is that we use multiple indicators of firm behaviour (market value, patents and R&D). This aids identification of the two spillover effects. Using a quite general framework, we develop the implications of technology and product market spillovers for each of these performance indicators[2]. We apply the approach to a panel of U.S. firms for

[1] This is not a new idea, but it has rarely been explicitly examined. Typically, earlier studies have assigned firms to a single, 'primary' industry because there is no information on the distribution of their sales activity across industries. The only previous, firm-level study that distinguishes technology and product market space is Jaffe (1988). Bransetter and Sakakibara (2002) use data on firm activities across industries in their analysis of RJVs, but they only do not have data on how much sales each firm has in each market.

[2] For an example of this multiple equation approach to identify the determination of techno-

the period 1981-2001. We find that that both technological spillovers and product market rivalry are present, and that R&D by product market rivals is a strategic complement for a firm's own R&D.

There are many examples in the business press where firms interact differently in technology and product market areas. For example, in the high end of the hard disk market, firms compete to offer different hard disks to computer manufacturers. Most firms base their technology on magnetic technologies, such as the market leader, Segway. Other firms (such as Phillips) are offering hard disks based on newer, holographic technology. These firms draw their technologies from very different areas, yet they compete in the same product market. R&D done by Phillips is likely to pose a competitive threat to Segway, even though it is unlikely to generate any knowledge spillovers for Segway. Other examples arise from situations where there is competition to establish standards in network-based industries, when those standards are based on distinct technologies.

The paper is organized as follows. The next section surveys some of the spillover literature. Section 3 outlines our modelling strategy. Section 4 discusses the econometric issues and Section 5 describes the data. The econometric findings are presented in Section 6. In the concluding remarks we summarize the key results and implications for future research.

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logical change see Griliches, Hall and Pakes (1991).

2. Spillovers Literature

Knowledge spillovers have been a major topic of economic research over the last thirty years. The theoretical literature considers the impact of externalities from R&D on strategic interactions between firms (e.g. Spence, 1984; Reinganum, 1989), as well as the role of spillovers in economic growth (e.g. Aghion and Howitt, 1992). Empirically, spillovers have been analyzed at the country, industry, firm and establishment level using a wide variety of techniques and data types[3] . More recently there has been a great deal of interest in international spillovers, both empirically and theoretically, in terms of their implications for growth and convergence in living standards[4].

There are several ways in which one firm's innovative activity can affect another firm's behaviour, so it is important to define exactly what is meant by 'knowledge spillovers'. Pure knowledge spillovers occur when innovation benefits not only the innovator, but 'spills over' to other firms by raising the level of knowledge upon which new innovations can be based. Several authors, following Griliches (1979), differentiate between pure knowledge spillovers and 'rent spillovers'. The latter occur for example when R&D-intensive inputs are purchased from other firms at less than their full 'quality' price. Such 'spillovers' are simply consequences of conventional measurement problems. In addition, innovation by competitors is likely to have strategic as well as productivity effects if it is embodied in new products or processes. For example other firms' R&D may have negative strategic

[3] For surveys see Griliches (1992), Mairesse (1995), or Hall (1996).
[4] For a recent surveys of empirical studies include Keller (2004).

effects because successful innovation can erode monopoly rents. Several studies have found evidence for such negative effects (Jaffe , 1986, and more recently Harhoff, 2000). But it hard to distinguish such spillovers from any other positive externality from innovation.

These issues make the identification of knowledge spillovers a difficult undertaking. The dominant approach to estimating knowledge spillovers over the last twenty years has been country, industry or firm-level regression-based estimates of returns to a measure of 'outside' R&D in a production (or cost) function framework. Other performance measures such as patenting have also been used. Aside from many problems associated with the estimation of production functions, the key difficulty for identification of spillovers is that the "spillover pool" of outside knowledge available to a firm must be specified *a priori*. This problem is concisely summed up by Griliches (1992): "To measure [spillovers] directly in some fashion, one has to assume either that their benefits are localised in a particular industry or range of products or that there are other ways of identifying the relevant channels of influence, that one can detect the path of the spillovers in the sands of the data."

A simple measure of the spillover pool available to a firm is the stock of knowledge generated by other firms in its industry. An example of this approach is Bernstein and Nadiri (1989) who use the unweighted sum of the R&D spending of other firms in the (two-digit) industry and find evidence of spillovers. However, there are several reasons why this may not be a good measure of the potential spillover pool available to a firm. It assumes firstly that firms only benefit from the R&D of firms in their industry, and secondly that all those firms' R&D is weighted equally in the construction of the spillover pool. In addition, measures based solely at the industry level risk picking up spurious results due to common industry trends or shocks unrelated to spillovers. More sophisticated approaches recognize that a firm is more likely to benefit from the R&D of other firms that are 'close' to it in some technological and/or geographical sense. In these models the 'spillover pool' available to firm i is equal to:

$$G_i = \Sigma_j w_{ij} R_j \tag{2.1}$$

where w_{ij} is some 'knowledge-weighting matrix' applied to the R&D expenditures of other firms or industries, R_j. All such (parametric) approaches impose the assumption that the spatial interaction between firms i and j is proportional to the weights (distance measure) w_{ij}.Pinkse, Slade and Brett (2002) develop a semi-parametric method for incorporating spatial interaction. This approach is more flexible since it does not impose any functional form assumption on how spatial interaction depends on the distance measure[5]. It could be applied in our context of identifying technological spillovers and product market rivalry, but in this paper we adopt the conventional parametric approach.

The literature contains many different approaches to constructing the knowledge-weighting matrix. A fairly common method, suggested by Griliches (1979) and first used in Jaffe (1986), is to use firm-level data on patenting by class of patent, or sometimes the distribution of R&D spending across product fields, to locate

[5]For a good review of this literature, see Slade (2003).

firms in a multi-dimensional technology space. A weighting matrix is then constructed using the uncentered correlation coefficients between the location vectors of different firms. Harhoff (2000) is a recent application of this approach that uses several different metrics. Another possibility is to use input-output flows (e.g. Scherer, 1982), although this method seems more likely to become contaminated by "rent spillover" effects.

Even in the absence of rent spillovers and strategic interactions between firms, these approaches to estimating spillovers suffer from a fundamental identification problem. This is that it is not easy to distinguish a spillovers interpretation from the possibility that any positive results are "just a reflection of spatially correlated technological opportunities" (Griliches, 1996). In other words, if new research opportunities arise exogenously in a firm's technological area, then it and its technological neighbors will do more R&D and may improve their productivity, an effect which will be erroneously picked up by a spillover measure.

This issue is discussed by Manski (1991, 2000) under the general title of "the reflection problem." True knowledge spillovers are an example of an endogenous social effect, where an individual outcome (e.g. productivity) varies with the behaviour of the group (e.g. R&D spending). This is distinct from an exogenous social effect, whereby an individual outcome varies with exogenous characteristics of the group, or a correlated effect where individuals in the same group have similar outcomes because they have similar characteristics or face similar environmental influences. Identification of endogenous effects is not possible without additional restrictions (Manski, 2000 for discussion). One certainly needs prior information that specifies the relevant reference group. This is the role played by a knowledge weighting matrix, or even a simple industry-level measure of the spillover pool. We place parametric structure on the nature of interactions through our firm specific pairings in technology space and product market space to achieve identification[6].

3. Analytical Framework

We consider the empirical implications of some simple R&D models with technological spillovers and strategic interaction in the product market. For analytical purposes, we distinguish between two basic models. The first is a non-tournament model of R&D where many firms can be simultaneously successful in their R&D investments. The second is a simple tournament model of R&D where there is a race for an infinitely lived patent. The latter introduces strategic considerations directly into the R&D game.

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 (positive) technological spillovers in this first stage. In stage 2, firms compete in some variable, say x, conditional on knowledge levels, k. We do not restrict the form of this competition except to assume Nash equilibrium. All that will matter for the analysis is whether there is some form of strategic interaction in the product market and whether it takes the form of

[6]The criticism of the method is that technological closeness is likely to be correlated with exogenous technological opportunity, and firms in the "cluster" may be subject to similar supply or demand shocks. We attempt to mitigate these problems by using lagged variables and conditioning on controls for the shocks (such as firm specific effects and industry demand). In any event, it is not obvious how such shocks would bias our estimates.

strategic substitution or complementarity. Even in the absence of technological spillovers, product market interaction creates 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.

We analyze a game with 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.[7]

Model 1. Non-tournament R&D competition

Stage 2

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

The best response for firms 0 and m are given by $x_0^* = \arg\max\ \pi(x_0, x_m, k_0)$ and $x_m^* = \arg\max\ \pi(x_m, x_0, k_m)$, respectively. Solving for second stage Nash decisions yields $x_0^* = f(k_0, k_m)$ and $x_m^* = f(k_m, k_0)$. First stage profit for firm 0 is $\Pi(k_0, k_m) = \pi(k_0, x_0^*, x_m^*)$, and similarly for firm m. If there is no strategic interaction in the product market, $\pi(k_0, x_0^*, x_m^*)$ does not vary with x_m and thus Π^0 do not depend on k_m.

[7] In reality, there is overlap between the firms in τ and m – the correlation between the technology (patents) and product market (sales) weighted R&D variables is about 0.4. We briefly consider issues arising from such overlap later.

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

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 (technological) externalities. We assume that the function ϕ is common to all firms.

Firm 0 solves the following problem:

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

Note that k_m does not involve r_0.The first order condition is:

$$\Pi_1\phi_1 - 1 = 0$$

where the subscripts denote partial derivatives with respect to the different arguments.[10] By comparative statics,

$$\frac{\partial r_0^*}{\partial r_\tau} = -\frac{\{\Pi_1\phi_{1\tau} + \Pi_{11}\phi_1\phi_\tau\}}{A} \tag{3.1}$$

[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. Recall that R&D spillovers will be introduced separately through the production of k. Certainly at $k_m \simeq 0$ this derivative must be negative, as monopoly is more profitable than duopoly.

[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 effects on its own profits.

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

$$\frac{\partial r_0^*}{\partial r_m} = -\frac{\Pi_{12}\phi_1}{A} \tag{3.2}$$

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). 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.[11]

We also get

$$\frac{\partial k_0}{\partial r_\tau} = \phi_2 > 0 \quad \text{and} \quad \frac{\partial k_0}{\partial r_m} = 0 \tag{3.3}$$

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 k measures the stock of patents. If the patenting decision is based on the potential market value of the

[11] This observation applies to single race models (see Chapter 10 in Tirole, 1994, for a review of these models) and more recent models of sequential races (Harris and Vickers, 1985; and Aghion, Harris and Vickers, 1997). There are some race models where this is not the case-e.g. if the R&D gap gets too wide between leader and follower and there is little chance of leapfrogging the follower may simply give up competing.

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 the following table

[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.[12]

Model 2. Tournament Competition

In this section we show that the predictions in Table 1 hold in a simple, stochastic patent race model with spillovers. We do not distinguish between com-

[12] To simply the model, we assumed that firms operate either in the same technology areas or the same product markets, but not both. What happens to the predictions of the model if we relax this assumption and allow for overlap in technology areas and product markets? Define the technology and market-related pools of outside R&D for firm i as

$$\begin{aligned} r_{i\tau} &= \sum_{j \neq i} s_{ij} r_j \\ &\text{and} \\ r_{im} &= \sum_{j \neq i} w_{ij} r_j \end{aligned}$$

where s and w represent some kind of technology and product market distance metrics, which we discuss in more detail in Section 4. The analysis in the text applies directly becasue it focuses on the effects of changes in these technology and product market R&D pools, $r_{i\tau}$ and r_{im}. However, if we want to analyze the effect of a change in the R&D of a *particular firm* (or set of firms), then we need to use the corresponding technology and market weights in doing that comparative statics exercise.

peting 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 may 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 does not depend directly on k_j.However, recall that in the context of a patent race, 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) $F = \pi^0(f(1,0), f(0,1); k_0 = 1) - \pi^0(f(0,1), f(1,0); k_0 = 0)$. We can write the expected value of firm 1 as

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

where R is the interest rate, r_m is the R&D spending of each of firm $0's$ rivals, and $h(r_0, r_m)$ is the probability that firm 0 gets the patent at each point of time given that it has not done so before (hazard rate). We assume that $h(r_0, r_m)$ is increasing and concave in both arguments. It is rising in r_m because of spillovers.[13] We also assume that $hF - R \geq 0$ (expected benefits per period exceed the opportunity cost of funds).

The best response function is given by $r_0^* = \arg\max\ V^0(r_0, r_m)$.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

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

By comparative statics and imposing symmetry, we find that

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

We assume that $h_{12} \geq 0$ (spillovers do not reduce the marginal product of a firm's R&D) and that $h_1F - 1 \geq 0$ (the expected net benefit of own R&D is

[13] 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.

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. This is because of the one shot nature of the game – the firms only race for a single patent.[14]

[14] 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.

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. 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}.

Firstly, 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 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[15], subject to the caveats we discuss below. Secondly, we have the issue of endogeneity due to transitory shocks. To mitigate these we condition on a full set of time dummies and a distributed lag of industry sales[16]. Furthermore we lag all the variables of interest on the right hand side of

[15] We have up to 21 years of continuous firm observations in our sample for estimation. In the market value equation, for example, the mean number of continuous time series observations is 16.

[16] The industry sales variable is constructed in the same way as the SPILLSIC variable. We

equation (4.1) by one year to overcome any immediate feedback effects[17]. Thirdly, 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 now discuss below.

4.2. Market Value equation

We adopt a simple linearization of the value function proposed by Griliches (1981)[18]

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

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

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

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.

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.

[17]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 this approach in the results section.

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

If $\gamma^v(G/A)$ was "small" then we could approximate $\ln\left(1+\gamma^v\left(\frac{G}{A}\right)_{it}\right)$ by $\left(\frac{G}{A}\right)_{it}$ .But this will not be a good approximation for many high tech firms[19] 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 $\phi((G/A)_{it-1})$), which is more computationally convenient when including fixed effects. We kept adding higher order terms until they were statistically insignificant at the 0.05 level. Empirically, we found that a fifth order series expansion was satisfactory. Taking into consideration the generic econometric issues over endogeneity discussed above, our basic empirical market value equation we estimate is:

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

4.3. R&D equation

We write the R&D equation as:

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

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

[19] See Hall and Oriani (2004) for example.

to the reflection problem (Manski, 1991). Any variable that shifts the incentive for firm i to perform R&D will also be likely to shift the incentive for firm j.A positive correlation could reflect strategic complementarity, but is could also reflect common unobserved shocks that are not controlled for by the other variables in (4.4).Our defences against this problem are: (a) we lag the independent variables, which should mitigate this problem (b) we include a variety of controls to account for the other factors driving this correlation and (c) we are particularly interested in the contrast between the coefficients on $SPILLTECH$ and $SPILLSIC$, which may, arguably, be less sensitive to the reflection problem.

4.4. Patent Equation

Because patents are counts, not continuous variables OLS is inappropriate. We use a version of the Negative Binomial count data model to allow for dynamics and fixed effects[20]. Models for count data generate the first moment of the form

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

where $E(.|.)$ is the conditional expectations operator. In our analysis we want to allow both for dynamics and fixed effects. To do so, we use a Multiplicative Feedback Model (MFM)[21]. The first moment of the estimator is:

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

[21] The short run impact of a variable on patents in the MFM is $E(P)\beta^P$.Alternative models, such as the Linear Feedback Model, generally have similar impacts as the MFM (Blundell et al, 1999, 2002). We are currently examining these alternatives.

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

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

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". Under Poisson $\alpha = 0$, restricting the mean to equal the variance. The Negative Binomial estimator relaxes this assumption (empirically, overdispersion is important in our data). We estimate the model by maximum likelihood.

We introduce firm fixed effects into the count data model using the "mean scaling" method of Blundell, Griffith and Van Reenen (1999) and Blundell, Griffith and Windmeijer. 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 a firm's patenting behaviour[22] and construct a pre-sample average stock of the firm's patenting. This initial condition can proxy for unobserved heterogeneity if the first moments of the variables are stationary. Although there will be some finite sample bias, Monte Carlo evidence shows that mean scaling estimator performs well compared to alternative econometric estimators for dynamic panel data models with weakly endogenous variables.

[22] We estimate from 1985 and use the information between 1968 and 1984 on patenting to construct the pre-sample means.

5. Data

The two main sources of data we use are: (1) accounting and market value data from Compustat, used to generate R&D, Tobin's Q and product market closeness measures; and (2) patent data from the U.S. Patent and Technology Office (USPTO), used to generate patent count, cite-weighted patents stock and technology market closeness measures. We now describe each data source and the construction of the two distance measures, $SPILLTECH$ and $SPILLSIC$,in more detail

5.1. Accounting Data and Product Market Closeness

The basic accounting and market value data come from U.S. Compustat 1980-2001. We cleaned the data to remove major mergers and acquisitions, accounting periods below ten months and above fourteen months, and firms with less than four years of consecutive data. R&D capital stocks were calculated using a perpetual inventory method with a 15% depreciation rate. We constructed a measure of Tobin's (average) Q as the total firm value divided by the full book value of assets, both following Hall, Jaffe and Trajtenberg (2000)[23].

The product market information is also provided by the Compustat from 1993 onwards, which reports the sales and 4-digit SIC codes of each major line of business. On average 5.1 different lines of business are reported per firm, ranging

[23]For Tobin's Q firm value is the sum of the values of common stock, preferred stock, long-term debt and short-term debt net of assets. Book value of capital includes net plant, property and equipment, inventories, investments in unconsolidated subsidiaries and intangibles (other than R&D). Tobin's Q was set to 0.1 for values below 0.1 and at 20 for values above 20. See also Lanjouw and Schankerman (2004).

from 1 to 28, covering 623 different 4-digit SIC codes. Taking the average share of sales per line of business within each firm over the period[24] is used as our measure of activity by product market, S_i, where $S_i = (S_{i,1}, S_{i,2}, ...S_{i,623})$ is the share of sales of firm i in each SIC code. The product market closeness measure is then calculated as the uncentered correlation between all firms pairings $SIC_{i,j}$ $(i \neq j)$, following Jaffe (1986), where

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

This closeness measure 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 competing, product-market R&D for firm i in year t, $SPILLSIC_{it}$,as

$$SPILLSIC_{it} = \Sigma_{j \neq i} SIC_{ij} R_{jt} \tag{5.1}$$

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

5.2. Patent Data and Technological "Closeness"

The U.S. Patent and Trademark Office patenting data come from the NBER data archive, described in Hall, Jaffe and Trajtenberg (2000). They drew this data from the United States Patent Office, and it contains detailed information on almost 3 million U.S. patents granted between January 1963 and December 1999, all citations made to these patents between 1975 and 1999 (over 16 million), and

[24] The breakdown by SIC code was unavailable prior to 1993, so we pool data 1993-2001. This is a shorter period than we have 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).

a firm level linking code for Compustat[25]. We kept all firm years with a positive patent stock (so those with current and/or previous patent counts) and matched by firm year into the cleaned Compustat data. This left a panel of 712 firms with accounting data between 1980 and 2001 and patenting data from 1970 to 1999.

The technology market information is provided by the allocation of all patents by the USPTO into 426 different technology classes (labelled N-Classes). Taking the average share of patents per firm in each technology class over the period 1970 to 1999 is used as our measure of activity by technology market, T_i, where $T_i = (T_{i,1}, T_{i,2}, ...T_{i,426})$ is the share of patents of firm i in each technology Class. The technological closeness measure is calculated, as above, as the uncentered correlation between all firms pairings $TECH_{i,j}$ $(i \neq j)$, where

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

This closeness measure ranges between zero and one, depending on the degree of technology market overlap[26] We construct the pool of technological spillover R&D for firm i in year t, $SPILLTECH_{it}$,as

$$SPILLTECH_{it} = \Sigma_{j \neq i} TECH_{ij} R_{jt}. \tag{5.2}$$

[25] A firm's patent stock is calculated using a perpetual inventory method with a deprecation rate of 15%. A citation weighted patent stock was also calculated, in which citations were normalized according to the average number of citations to all patents in that year, with the stock again calculated using a perpetual inventory method. See Hall, Jaffe and Trajtenberg (2000) and Bloom and Van Reenen (2001).

[26] 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 more accurately pin down the firm's position.

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 there is huge heterogeneity in size, as well as in R&D intensity, patenting activity and market valuation. The two closeness measures also differ widely across firms [27] It is worth noting that the bulk – about 80 percent – of the variance in the associated pools of external (technological and product market) R&D, $SPILLTECH$ and $SPILLSIC$, is between-firm variance. This means that introducing fixed firm effects in the econometric specifications, as we will do, will leave only about 20 percent of the variance to identify the spillover effects of interest.

[Table 2 about here]

5.3. Identification from Product Market and Technology Distance Measures

In order to distinguish between the effects of technology spillovers and strategic interaction in product markets we must have variation in the distance metrics in technology space and product market space. If these two dimensions are empirically strongly collinear - so that the overlap between any pair of firms in technology space and product market space are very close - identification of differential impacts will not be feasible. So the initial empirical question that needs to be addressed before we undertake any estimation is: How distinct are our measures

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

of technology and product market closeness, SIC and $TECH$?.

To gauge this we do three things. First, we calculate the raw correlation between the two measures (SIC and $TECH$). This correlation is only 0.47, which suggests that the two measures reflect different characteristics of firms and gives some hope of empirical identification. After weighting these with R&D stocks using equations (5.2) and (5.1) the correlation between $SPILLTECH$ and $SPILLSIC$ is only 0.42 in the cross sectional dimension. Of course when controlling for fixed effects we rely on the within firm variation so the relevant correlation is in the change of $SPILLTECH$ and $SPILLSIC$ which is only 0.17. Second, we plot the two measures against each other in Figure 1. Two features are noteworthy. It is apparent that the positive correlation we observe is caused by a wide dispersion across the unit box, rather than being driven by a few outliers. There is a large mass of firms which are far from each other both in technology and product space (bottom left quadrant) and a smaller mass of firms which are close on both dimensions (top right quadrant). However, there is also a large mass of firms, in the top left quadrant, which are close product market competitors but draw their technology from very different technology areas. There is also a significant number of firms which are close in technology space but compete in very different product markets (bottom right quadrant). In the Appendix 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 spaces.

6. Results

6.1. 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 3, we use a series expansion in the own R&D to capital stock ratio to capture the nonlinearity in the value equation, because it is easier to incorporate fixed effects in this specification[28]. The coefficients of the other variables in column (1) were close to those obtained from nonlinear least squares estimation[29]. 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.

Including firm fixed effects in column (2) changes the estimated coefficients in several ways[30]. Recall that we include a fifth-order series of the ratio of own-R&D stock to tangible capital, G/A,in order to capture the nonlinearity in the

[28] The coefficient on the sixth order term in G/K was insignificant (p-value 0.63) in column (2).

[29] For example, using NLLS, the coefficients (standard errors) on $SPILLTECH$ and $SPILLSIC$ were -0.043 and 0.046, respectively (compared to -0.046 and 0.045 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).

[30] The fixed effects are highly jointly significant, with F(702,11946)=27.9 and a p-value $<$ 0.001. The Hausman test also rejects the null of random effects plus three digit dummies vs. our fixed effects specification (p-value=0.029).

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 0.176. A ten percent increase in the stock of R&D for the firm increases its market value by about 1.8 percent. Evaluated at the sample means, this implies that an extra dollar of R&D is worth about 87 cents 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 extremely close to the 86 cent figure obtained by Hall, Jaffe and Trajtenberg (2000) over an earlier sample period.

When we allow for fixed effects, the estimated coefficient on $SPILLTECH$ switches signs and becomes positive and significant as compared to column (1). A ten percent increase in $SPILLTECH$ generates a 1.5 percent increase in market value. At sample means, this implies that an extra dollar of $SPILLTECH$ increases the recipient firm's market value by 2.6 cents. Put another way, 2.6 cents is the amount by which the market value of a firm would rise if another firm with perfect overlap in technology areas ($SIC = 1$) raised its R&D by one dollar. Comparing this figure to the return from own-R&D (86 cents), we conclude that the private value of a dollar of technological spillover is only worth (in terms of market value) about 3 percent as much as a dollar of own R&D[31].

With fixed effects, the estimated coefficient on $SPILLSIC$ is now negative

[31] We also experimented with including the interaction between $ln(SPILLTECH)$ and G/K to test for "absorptive capacity" (are spillovers larger for R&D intensive firms). Although positive this was insignificant when we control for fixed effects (0.013 with a standard error of 0.012)

and significant at the five percent level, rather than being positive and significant. Evaluated at the sample means, a ten percent increase in $SPILLSIC$ generates a 0.43 percent reduction in market value. At sample means, this implies that an extra dollar of $SPILLSIC$ reduces a firm's market value by 2.8 cents. Interestingly, the negative impact of an extra dollar of product market rivals' R&D is broadly the same magnitude as the positive impact of a dollar of technological (R&D) spillovers. Of course, the net effect of R&D spending by other firms will depend on the product market and technological distance between those firms ($TECH$ and SIC). Using our parameter estimates, one could compute the effect of an exogenous change in R&D for any specific sets of firms.[32]

In short, once we allow for fixed firm effects 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 technological 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 technological 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

[32] In doing such simulation exercises, it would be necessary to include the strategic reaction of a firm's R&D spending to product market rivals. As we discuss later in this section, we find that R&D by product market rivals is a strategic complement, so increases in that pool would induce greater R&D by the firm.

level. Thus failing to control for product market rivalry would lead us to miss the impact of technological spillovers on market value. The same bias is illustrated for $SPILLSIC$ - if we failed to control for technological spillovers we would find no 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 when we introduce fixed effects is not due to measurement error. 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 Qs (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 (they are like more accurate industry or technology dummies)[33].

[33] Finally, 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 0.140 (0.071) and on $SPILLSIC$ of -0.047 (.024).

6.2. 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[34]. $SPILLTECH$ 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 (and in other columns), 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 (the control for fixed effects is 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 2.9 percent increase in patents. The estimated elasticity of 0.289 points to more sharply diminishing returns than most previous estimates in the literature, but the earlier studies do not typically control for technological spillovers or the level 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 .008 extra patents – equivalently, the cost of the marginal patent produced by own R&D is about $125,000.

Turning to our key variables, allowing for fixed effects reduces the coefficient on

[34] We also tried weighting the patent counts by future citations, but this made little difference to the main results.

$SPILLTECH$, 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 technological spillovers generates .00017 extra patents. Comparing this figure to the figure for own-R&D, we conclude that a dollar of technological spillovers is only worth 21 percent as much to a firm as a dollar of its own R&D (in terms of extra patents generated).

Finally, in column (3) we present our preferred specification, which includes both firm fixed effects and lagged patent counts[35]. 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 highly significant coefficient. Note that these results do not depend on the distributional assumptions underlying the Negative Binomial model. Using a GMM estimator that relies only on the first moment condition and allowing general heteroskedacity over units and across time, leads to qualitatively similar results[36].

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.

[35]The pre-sample estimator assumes we can capture all of the fixed effect bias by the long pre-sample history of patents (usually 16 years). To check on 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.

[36]In particular $SPILLTECH$ and lagged R&D were positive and significant and $SPILLSIC$ was insignificant.

6.3. R&D Equation

We now turn to the parameter estimates for the R&D equation (Table 5). In the static specification without firm fixed effects (column (1)), we find that both technological and product market spillovers are present[37]. 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 positively affects R&D spending at the firm level. 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. The same conclusions hold when we allow for dynamics (lagged R&D) and the implied, long run effect are similar in magnitude to the static specification.

To summarize, we find strong evidence that R&D spending by a firm and its *product market rivals* are strategic complements, even once we control for industry level sales and firm fixed effects.

The only other study that tries to test whether R&D games exhibit strategic complementarity, to our knowledge, is Cockburn and Henderson (1995). They

[37] 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 the fixed effects model at the ($\chi^2(25) = 52.60$,p-value=0.022).

study detailed R&D data from ten major pharmaceutical companies and find that R&D investment is only weakly correlated across firms, once common responses to exogenous shocks are taken into account. They interpret this as rejecting the hypothesis that R&D investment in that industry is driven by strategic considerations. However, as we argued in Section 3, identifying the role of strategic rivalry and R&D spillovers really requires the use of multiple outcome measures – in our case, market value, patents and R&D. Attempts to do so with a single performance indicator, as in Cockburn and Henderson (1995), are problematic.

To summarize our findings concisely, Table 6 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 technological spillovers and product market rivalry.

6.4. An extension to Productivity

We close this discussion with a preliminary set of results on the productivity impact of technological and product market spillovers. To do that, we estimate a Cobb Douglas production incorporating the two spillover variables. The predicted coefficients on the these spillover measures depends on the quality of the price deflators used to measure real output. If the price deflators are good, then we would expect technological spillovers to increase output (given the levels of capital, labour and R&D inputs) because they increase productivity of R&D by the firm.

However, product market spillovers should have no direct effect on productivity, even though they would affect the optimal levels of inputs. If our output measure is contaminated by prices, then the predictions are less clear – in that case we might expect to find that R&D by product market rivals also affects (mis)measured productivity, and the impact of technological spillovers will also contain demand-elasticity effects (Klette and Griliches, 1996). In the empirical work we use time dummies and three digit industry specific deflators to pick up price movements.

These results should be interpreted with caution for two reasons. First, there is a misspecification due to data availability. Specifically, we measure output by sales but we do not have a measure of intermediate material inputs. This will create an upward bias in the estimated spillover effects if intermediate inputs (quantity or quality) are positively related to technological or product market spillovers. The bias may not be too serious, since we would expect the relevant R&D here would be the R&D by input *suppliers*. The second limitation is that we estimate by OLS, rather than using more sophisticated techniques to allow for input endogeneity (this will be done in later versions).

Table7 summarizes the results. In the specification without firm fixed effects (column 1), we estimate the output elasticity of own R&D at 0.054, which is in line with the literature. But we find no significant effects for $SPILLTECH$ and a significant negative correlation of productivity with $SPILLSIC$. However, when we allow for fixed effects the results change. The estimated coefficient on own R&D is robust to fixed effects, but now we find that technological spillovers have a positive and statistically significant impact on productivity. Product market rivals' R&D, $SPILLSIC$, has no significant association with measured productivity.

7. Policy Simulations

[to follow]

8. Conclusions

R&D activity of other firms generates two basic types of spillovers to other firms. Benefits accrue from technological spillovers, but R&D by product market rivals can have strategic business stealing effects. We propose a simple methodology for identifying these two effects, which is based on two features. First, we distinguish a firm's position in *technology* space and *product market* space. Second, we use multiple indicators of performance (market value, patents and R&D). Using a quite general framework, we develop the implications of technology and product market spillovers for these different indicators. We apply the approach to a large panel of U.S. firms from Compustat for the period 1981-2001. We find that that both technological spillovers and product market rivalry are present in our data, and that R&D by product market rivals is a strategic complement for a firm's own R&D. The results are consistent with theoretical predictions when R&D is a strategic complement, and indicate that both strategic rivalry and R&D knowledge spillovers are present. We show that failure to control for product market rivalry will lead to an underestimation of the magnitude of technological spillovers (e.g. in the market value equation).

There are many extensions and robustness checks we need to pursue. We are currently looking at the heterogeneity between industries of our results, other econometric methods of controlling for endogeneity, the impact of additional control variables (e.g. for product market structure) and examining alternative ways of constructing our spillover measures. Nevertheless, we believe the framework and results in this paper offer a fruitful method for dealing with a long-standing problem in the empirical literature.

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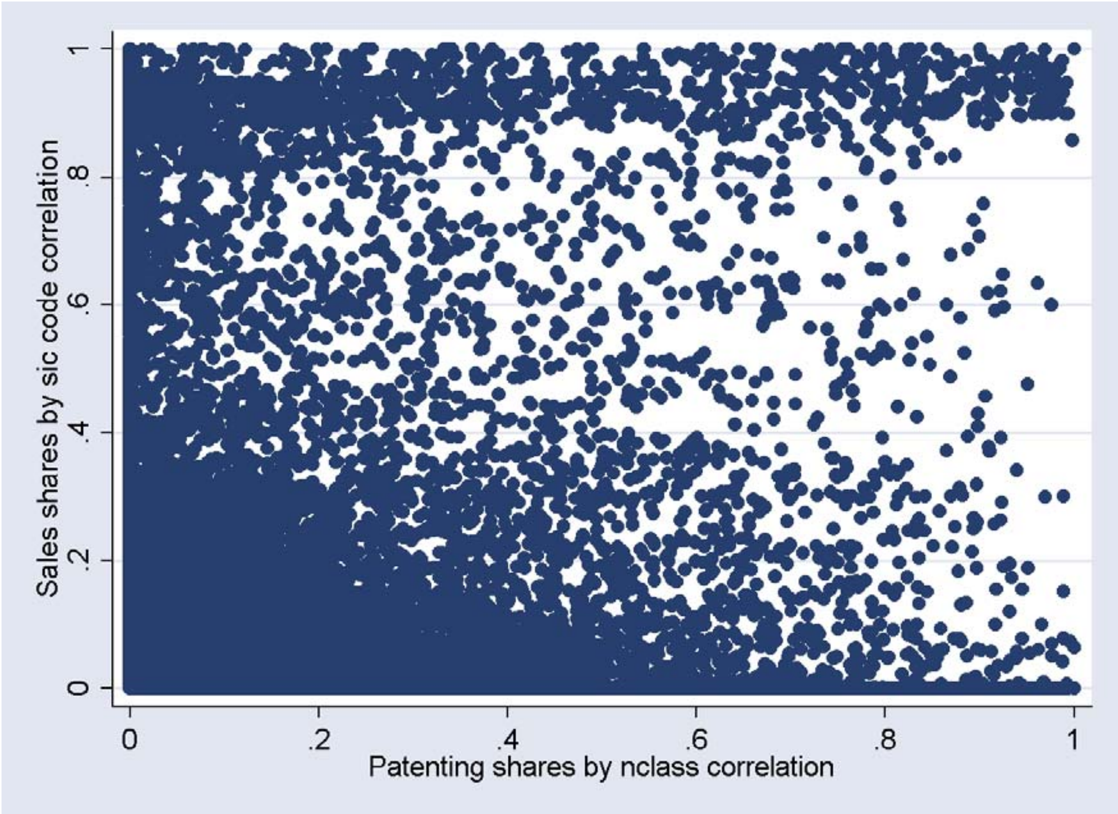

Figure 1: SIC and TEC correlations

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	No Technological Spillovers	Some Technological Spillovers	Some Technological Spillovers
		Strategic complements	Strategic Substitutes	Strategic complements	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	Positive
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Positive	Negative	Positive	Negative

Notes: See text for derivations of comparative statics

Table 2: Descriptive Statistics

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

Notes: The means, medians and standard deviations are taken over all non-missing observations between 1981 and 2001 (observations vary between 13,726 and 14,542)

Table 3: Coefficient Estimates for Tobin's-Q Equation

Dependent variable: Ln (V/A)	(1)	(2)	(3)	(4)
	No individual Effects	Fixed Effects	Fixed Effects (drop SPILLSIC)	Fixed Effects (drop SPILLTEC)
Ln($SPILLTECH_{t-1}$)	-0.046 (0.028)	0.149 (0.066)	0.116 (0.064)	
Ln($SPILLSIC_{t-1}$)	0.045 (0.015)	-0.043 (0.021)		-0.033 (0.020)
Ln(Industry $Sales_t$)	0.330 (0.072)	0.197 (0.041)	0.196 (0.041)	0.199 (0.041)
Ln(Industry $Sales_{t-1}$)	-0.413 (0.070)	-0.148 (0.042)	-0.153 (.041)	-0.140 (0.042)
Ln(R&D Stock/Capital $Stock)_{t-1}$	0.945 (0.196)	0.351 (0.111)	0.348 (0.111)	0.359 (0.111)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^2$	-0.290 (0.173)	0.043 (0.091)	0.047 (0.091)	0.043 (0.091)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^3$	0.040 (0.055)	-0.042 (0.028)	-0.043 (0.028)	-0.042 (0.028)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^4$	-0.002 (0.007)	0.007 (0.004)	0.007 (0.004)	0.007 (0.004)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^5$	0.001 [a] (0.031)	-0.034[a] (0.015)	-0.035 [a] (0.015)	-0.034 [a] (0.015)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects (703)	No	Yes	Yes	Yes
No. Observations	12,673	12,673	12,673	12,673
R^2	0.192	0.694	0.674	0.694

[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 (robust standard errors in brackets). The non fixed effects column (1) also allows for clustering of standard errors by firm. A dummy variable is included for observations where lagged R&D stock equals zero. The estimation period is 1981-2001.

Table 4: Coefficient Estimates for the Patent Equation

Dependent variable: Patent Count	(1)	(2)	(3)	(4)
	No initial conditions: Static	Initial Conditions: Static	Initial Conditions: Dynamics	Initial Conditions: Dynamics
Ln(SPILLTECH) $_{t-1}$	0.342 (0.079)	0.237 (0.070)	0.157 (0.035)	0.164 (0.035)
Ln(SPILLSIC) $_{t-1}$	0.064 (0.032)	0.072 (0.029)	0.027 (0.016)	
Ln(R&D Stock) $_{t-1}$	0.502 (0.043)	0.289 (0.044)	0.105 (0.025)	0.106 (0.025)
Ln(Sales) $_{t-1}$	0.335 (0.052)	0.222 (0.045)	0.113 (0.024)	0.115 (0.024)
Ln(Patents) $_{t-1}$			0.571 (0.026)	0.572 (0.027)
Pre-sample fixed effect		0.472 (0.043)	0.179 (0.025)	0.177 (0.024)
Over-dispersion (alpha)	1.087 (0.070)	0.885 (0.050)	0.415 (0.030)	0.416 (0.030)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects (682)	No	Yes	Yes	Yes
No. Observations	8,444	8,444	8,444	8,444
Log Pseudo Likelihood	-20,240	-19,739	-18,166	-18,168

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. The estimation period is 1985-1998. 3-digit SIC dummies are included in all columns. A dummy variable is included for observations where lagged patent stock equals zero (column (3) or lagged R&D stock equals zero (all columns). 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) and Blundell, Griffith and Windmeijer (2002) – see text.

Table 5: Coefficient Estimates for the R&D Equation

Dependent variable ln(R&D)	(1)	(2)	(3)	(4)
	No Effects	Fixed Effects	Fixed Effects + Dynamics	Fixed Effects + Dynamics
Ln(SPILLTECH) $_{t-1}$	0.225 (0.017)	0.119 (0.072)	0.018 (0.040)	
Ln(SPILLSIC) $_{t-1}$	0.292 (0.012)	0.109 (0.026)	0.025 (0.013)	0.027 (0.013)
Ln(Sales) $_{t-1}$	0.796 (0.009)	0.801 (0.017)	0.217 (0.015)	0.217 (0.015)
Ln(R&D) $_{t-1}$			0.695 (0.015)	0.695 (0.015)
Ln(Industry Sales) $_t$	0.699 (0.083)	0.134 (0.030)	0.134 (0.022)	0.134 (0.022)
Ln(Industry Sales) $_{t-1}$	-0.879 (0.083)	-0.082 (0.031)	-0.108 (0.023)	-0.107 (0.022)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects (536)	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. Estimation period is 1981-2001.

Table 6: 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	.144*	Yes
$\partial V_0/\partial r_m$	Market value with SPILLSIC	Negative	-.043*	Yes
$\partial k_0/\partial r_\tau$	Patents with SPILLTECH	Positive	.157*	Yes
$\partial k_0/\partial r_m$	Patents with SPILLSIC	Zero	.027	Yes
$\partial r_0/\partial r_\tau$	R&D with SPILLTECH	Ambiguous	.018	-
$\partial r_0/\partial r_m$	R&D with SPILLSIC	Positive	.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 5% level.

Table 7: Coefficient Estimates for the Production Function

Dependent variable Ln(Sales)	(1)	(2)	(3)
	No Effects	Fixed effects	Fixed effects
Ln(SPILLTECH) $_{t-1}$	-0.040 (0.08)	0.160 (0.038)	0.158 (0.037)
Ln(SPILLSIC) $_{t-1}$	-0.010 (0.003)	-0.002 (0.011)	
Ln(Capital) $_{t-1}$	0.297 (0.008)	0.179 (0.010)	0.179 (0.010)
Ln(Labour) $_{t-1}$	0.641 (0.011)	0.634 (0.013)	0.634 (0.013)
Ln(R&D Stock) $_{t-1}$	0.054 (0.005)	0.041 (0.006)	0.041 (0.006)
Ln(Industry Sales) $_t$	0.187 (0.036)	0.181 (0.021)	0.181 (0.021)
Ln(Industry Sales) $_{t-1}$	-0.073 (0.036)	-0.026 (0.021)	-0.026 (0.021)
Ln(Industry deflator) $_t$	-0.041 (0.047)	0.094 (0.033)	0.094 (0.033)
Year dummies	Yes	Yes	Yes
Firm fixed effects (711)	No	Yes	Yes
No. Observations	12,663	12,663	12,663
R^2	0.948	0.988	0.988

Notes: Estimation is by OLS. Standard errors (in brackets) are robust to arbitrary heteroskedacity and allow for clustering by firm in the non fixed effects column (1). A dummy variable for observations where lagged R&D equals to zero is included. Estimation period is 1981-2001.