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

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July 5, 2004

Abstract

Firm performance is affected in two ways by 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 effect, 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 panel of U.S. firms for 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.

Status: Preliminary: Do not Quote. Comments welcomed.

JEL No. O32, O33, F23

Keywords: knowledge spillovers, strategic rivalry, R&D, market value, patents

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*****Acknowledgement:** The authors would like to thank Jan Boone for helpful comments. Financial support for this project was provided by the ESRC Centre for Economic Performance.

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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. 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. This paper develops a methodology for identifying the separate effects of technological and product market spillovers.

But it is important to identify the empirical impact of these spillovers for 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.

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 and sales activity. 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 performance (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. We apply the approach to a panel of U.S. firms for 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

[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).

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.

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[2] . 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[3].

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 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

[2] For surveys see Griliches (1992), Mairesse (1995), or Hall (1996).

[3] For a recent surveys of empirical studies include Keller (2001).

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 weighs (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. For a good review of this literature, see Slade 2003). This approach 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 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) under the general title "the reflection problem". True knowledge spillovers correspond to an endogenous social effect, in the sense that an individual outcome (e.g. productivity) varies with the behaviour of the group (e.g. R&D spending). This can be differentiated from an exogenous social effect, whereby an individual outcome varies with the exogenous characteristics of the group, or a correlated effect whereby individuals in the same group tend to have similar outcomes because they have similar characteristics or face similar environmental influences. Identification of endogenous effects is not possible unless prior information is available with which to specify the composition of reference groups. This is the role played by a knowledge weighting matrix, or even a simple industry-level measure of the spillover pool. However, even if this information is available, identification is not possible if the variables defining reference groups are functionally related to variables that directly affect outcomes. This is quite likely to be the case for many of the approaches found in the literature. For example, technological closeness is likely to be correlated with exogenous technological opportunity, and firms in the same industry are likely to be subject to similar supply or demand shocks. Thus the task for anybody trying to identify knowledge spillovers is to find a set of variables with which to define firms' reference groups that are not related to unobserved variables that directly affect the outcomes being measured.

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 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.[4]

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 1 (e.g. product innovation), its profits would increase for any given level of price or output in the second stage.[5]

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. The assumption that $\Pi(k_0, k_m)$declines in k_m is reasonable unless innovation cre-

[4] 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 0.3. We briefly consider issues arising from such overlap later.

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

ates 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.

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:

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

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.[6] By comparative statics,

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

[6] 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

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

Thus firm $1's$ 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.[7]

We also get

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

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

[7] 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).

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. R&D Spillovers and Strategic Rivalry: Non-Tournament

	R&D			
	No R&D Spillovers Strategic Complements	No R&D Spillovers Strategic Substitutes	R&D Spillovers Strategic Complements	R&D Spillo Strategic Su
$\frac{\partial V_0}{\partial r_\tau}\|_{r_0}$	Zero	Zero	Positive	Positive
$\frac{\partial V_0}{\partial r_m}\|_{r_0}$	Negative	Negative	Negative	Negative
$\frac{\partial k_0}{\partial r_\tau}$	Zero	Zero	Positive	Positive
$\frac{\partial k_0}{\partial r_m}$	Zero	Zero	Zero	Zero
$\frac{\partial r_0}{\partial r_\tau}$	Zero	Zero	Ambiguous	Positive
$\frac{\partial r_0}{\partial r_m}$	Positive	Negative	Positive	Negative

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.[8]

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 competing firms in the technology and product markets because the distinction does

[8] 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

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

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.

$\partial\Pi^i(k_i, k_j)/\partial k_j < 0$.

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.[9] 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

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

[9] 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.

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

Using the envelope theorem,

$$\frac{\partial V^0}{\partial r_m}|_{r_0} < 0$$

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.[10]

[10] 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, 1979) is likely to be small[11], subject to the caveats we discuss below. Secondly, 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[12]. Furthermore we lag all the firm level variables on the right hand side

[11] 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.

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

of equation (4.1) by one period to overcome any immediate feedback effects[13]. 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)[14]

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

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.

[13] 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.

[14] 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[15] 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[16] our basic empirical market value equation we estimate is:

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

4.3. R&D equation

We write the R&D equation as:

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

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

[16] We do not include a lagged dependent variable as this would make our specification close to a first difference equation in market value where only "surprises" should matter. This is qualitatively different in interpretation from the "hedonic" equation that we are estimating here.

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). 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[17]. 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

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

Feedback Model (MFM)[18]. The first moment of the estimator is:

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

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 model using two alternative approaches: Hausman, Hall and Griliches (1984), which is valid when the regressors are strictly exogenous, and Blundell, Griffith and Van Reenen (1999), which relaxes this assumption[19].

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

[18] 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.

[19] See also Blundell, Griffith and Windmeijer (2002)

(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)[20].

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 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[21] is used as our measure

[20] 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).

[21] 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).

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 a firm level linking code for Compustat[22]. We kept all firm years with a positive

[22] 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).

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[23] We construct the pool of technological spillover R&D for firm i in year t, $SPILLTECH_{it}$,as

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

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

[23] 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 oin down the firm's position.

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 [24] 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. Descriptive Statistics

Variable name	Mnemonic	Mean	Median	s.d
Tobins Q	V/K	2.36	1.41	3.00
Market value	V	4,013.5	414.3	16,702
R&D stock	G	616.4	28.0	2,764.7
R&D stock/fixed capital	G/K	0.48	0.18	0.92
R&D flow	R	79.5	1	2,10.5
Technological Spillovers	SPILLTECH	6,006.5	1,019.8	93,14.7
Product market rivalry	SPILLSIC	9,989	293.0	10,710.3
Patent flow	P	7.9	0	54.9
Sales	S	3,111.1	478	9,824.9
fixed capital	K	1,176.3	11,76.3	4,155.1

*Notes:*The means, medians and standard deviations are taken over all non-missing observations (up to 16,310) between 1980-2001.

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

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

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 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 0.213, which suggests that the two measures reflect different characteristics of firms and gives some hope of empirical identification. Even after weighting these with R&D stocks using equations (5.2) and (5.1) the correlation between $SPILLTECH$ and $SPILLSIC$ is still only 0.309. 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 four examples of well-known firms, from both low and high-tech sectors, to illustrate the four possible pairings – near/far in product market and 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[25]. The coefficients of the other variables in column (1) were close to those obtained from nonlinear least squares estimation[26]. In this specification without any firm fixed effects, the product market spillover variable, $SPILLSIC$,has a positive impact on market value of the firm, contrary to the prediction of the theory. Finally, we find that the *growth* of industry sales affects the firm's market value (the coefficients are close to being equal and opposite), which probably reflects unobserved demand factors.

Including firm fixed effects in column (2) changes the estimated coefficients in several ways[27]. The coefficient on own R&D is twice as large when we allow

[25] The coefficient on the sixth order term in G/K was insignificant (p-value 0.546) in column (2).

[26] For example, the coefficients (*standard errors*) on $SPILLTECH$ and $SPILLSIC$ were 0.034(*0.006*) and 0.047(*0.004*) respectively under NLLS. If we estimate using OLS and using just the first order term of G/A, the coefficients(*standard errors*) on G/A was 0.275(*0.011*) compared to 0.775(*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%.

[27] The fixed effects are highly jointly significant with an F(702,11942)=28.01 and a p-value of under 0.001. The Hausman test also rejects the null of random effects with a p-value of under 0.001 ($\chi^2(28) = 91.70$). The Hausman test does not reject a random effects specification including four digit dummies vs. our fixed effects specisifcation (conditional on strict exogeneity). But

for fixed effects. 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 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 0.175. A ten percent increase in the stock of R&D for the firm increases it market value by about 1.75 percent. Evaluated at the sample means, this implies that an extra dollar of R&D is worth about 86 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 almost identical to the finding by Hall, Jaffe and Trajtenberg (2000).

When we allow for fixed effects, the estimated coefficient on $SPILLTECH$ remains positive but is more than three times as large, as compared to column (1). A ten percent increase in $SPILLTECH$ generates a .76 percent increase in market value. At sample means, this implies that an extra dollar of $SPILLTECH$ increases the recipient firm's market value by 5.1 cents. Put another way, 5.1 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 a dollar of technological spillover R&D is worth (in terms of market value) about 5.8 percent as much to a firm as a dollar of its own R&D[28].

examination of our the coefficients shows that there are significant differences between random and fixed effects for our variables of interest. For example, the difference in the $SPILLTECH$ coefficient is 0.024 with a standard error of 0.009.

[28] We also experimented with including the interaction between $ln(SPILLTECH)$ and G/K to test for "absorbtive capacity" (are spillovers larger for R&D intensive firms). As with Jaffe

With fixed effects, the estimated coefficient on $SPILLSIC$ is now negative and significant at the ten percent level[29]. Evaluated at the sample means, a ten percent increase in $SPILLSIC$ generates a 0.39 percent reduction in market value. At sample means, this implies that an extra dollar of $SPILLSIC$ reduces a firm's market value by 1.6 cents. It is interesting to note that the negative impact of an extra dollar of product market rivals' R&D is much smaller than the positive impact 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.[30]

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

(1986) this interaction was positive and significant for OLS (.022 with a standard error of 0.007). It was insignificant in the fixed effects specifications, however.

[29] The coefficients on $SPILLTECH$ and $SPILLSIC$ are also *jointly significant* at the 5% level; the test statistic is F(2,11,946) = 3.12 (p-value = 0.04).

[30] 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.

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. Thus failing to control for product market rivalry would lead us to miss the impact of technological spillovers on market value.

Attenuation bias is exacerbated by fixed effects, but classical measurement error should bias the coefficient 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 (one coefficient rises while the other declines). 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 $SPILLTECH$ and $SPILLSIC$ and high Tobin's Qs (since R&D will not perfectly control for intangible knowledge stocks). This will drive a positive correlation between the spillover terms 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).

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 0.064 (*.044*) and on $SPILLSIC$ of -.042 (*.023*)[31].

6.2. Patents Equation

We turn next to the patents equation (Table 4). Column (1) presents the OLS estimates in a static model. Unsurprisingly, larger firms and those with larger R&D stocks are much more likely to have more patents[32]. $SPILLTECH$ has a positive and highly significant association with patenting, indicating the presence of technological spillovers. By contrast, there is no evidence of product market rivalry effects on patenting – the coefficient on $SPILLSIC$ is insignificant. These findings are in line with the theory outlined in Section 3. 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. We can easily reject the hypothesis that there are no firm effects (p-value under 0.001). Compared to column (1), the coefficient on the R&D stock falls by about half but remains highly significant. A ten percent increase in the stock of own R&D generates a 2.2 percent increase in patents. This estimate 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 .0029 extra patents – equivalently, the cost of the marginal

[31] This approach instruments all the firm level variables and the spillover variables. We also used the Arellano-Bover (1995) approach of instrumenting with the lagged differences.

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

patent produced by own R&D is about \$344,000.

Turning to our key variables, allowing fixed effects reduces the coefficient on $SPILLTECH$,but it remains positive and significant at the .05 level. The estimated coefficient on $SPILLSIC$ remains insignificant. Evaluated at the sample means, the estimates for $SPILLTECH$ imply that an extra dollar of technological spillovers generates .00027 extra patents. Comparing this figure to the figure for own-R&D, we conclude that a dollar of technological spillovers is worth (in terms of extra patents generated) about 10 percent as much to a firm as a dollar of its own R&D.

The coefficient on firm sales variable rises sharply when we add firm fixed effects, and remains significant. Our finding that higher sales is associated with increased patenting activity, conditional on the R&D variables, is consistent with the idea that greater demand[33] makes an innovation more valuable and thus more likely to pass the threshold to justify incurring the costs of patenting.

Finally, in column (3) we present our most demanding specification, which includes both firm fixed effects and lagged patent counts. Not surprisingly, we find persistence in patenting (the coefficient on lagged patents is highly significant), but the main findings from the static model do not change when we add dynamics. We obtain a similar pattern of implied, long run effects of the other variables[34].

[33] Including industry sales was unnecessary as the current and lagged values were individually and jointly insignificant ($\chi^2(2) = 4.42$) with a p-value of 0.11.

[34] We also used the Blundell, Griffith and Van Reenen (1999) approach of conditioning on the initial conditions to control for correlated unobserved heterogeneity. We included the average value of the pre-sample patent stock (1969-1980) in the context of the specification in column (3). This variable was highly significant, with a coefficient (standard error) of 0.148 (.013).$SPILLTECH$ remained highly significant, with coefficient of 0.160 (.014) and

Dropping the insignificant $SPILLSIC$ variable from column (3) increases the coefficient on $SPILLTECH$ to 0.252 with a standard error of 0.113 (see column (4)).

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.

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[35]. 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 0.70) and highly significant.

But as in the market value equation, the inclusion of firm fixed effects (column (2)) changes the key results. In this case the coefficient on $SPILLSIC$ remains positive and highly significant, indicating strategic complementarity, but the coefficient on $SPILLTECH$ disappears. Introducing dynamics (lagged R&D) reduces the precision of the estimates, but does not change the magnitude or statistical

$SPILLSIC$ remained insignificant.

[35]The fixed effects are highly significant (p-value under .001). A Hausman Test of random effects with four digit industry dummies is rejected in favour of the fixed effects model at the 0.01 level ($\chi^2(25) = 52.60$)).

significance of the implied, long run coefficients on the two spillover variables. 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.

And yet, even though the finding of strategic complementarity is robust, the direct (short run) impact of product market rivals' R&D is relatively small. Using the estimated elasticity of 0.109 (column (2) in Table 3) and evaluating at sample means, we find that an extra dollar of $SPILLSIC$ raises a firm's own R&D spending by only 0.082 cents. However, we emphasize that this is only a short run impact because it ignores the feedback effect of an increase in own R&D on the R&D by rival firms, and so on. To assess the long run impact, we need to have a model of how the equilibrium level of R&D is determined and use it for policy simulation.

The only other study that tries to test whether R&D games exhibit strategic complementarity, to our knowledge, is Cockburn and Henderson (1995). They 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 1-3. 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.

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

Dependent variable: Ln (V/A)	(1)	(2)	(3)
	No individual Effects	Fixed Effects	Fixed Effects (drop SPILLSIC)
Ln($SPILLTECH_{t-1}$)	.022 (.006)	.076 (.042)	0.062 (0.041)
Ln($SPILLSIC_{t-1}$)	.034 (.004)	-.039 (.020)	
Ln(Industry $Sales_t$)	.328 (.061)	.197 (.041)	0.196 (.041)
Ln(Industry $Sales_{t-1}$)	-.413 (.061)	-.146 (.042)	-.151 (.042)
Ln(R&D Stock/Capital $Stock)_{t-1}$	.171 (.023)	.354 (.112)	.350 (.112)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^2$	-.267 (.081)	.035 (.092)	.039 (.092)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^3$	.037 (.029)	-.039 (.028)	-.040 (.028)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^4$	-.002 (.004)	.007 (.004)	.007 (.004)
[Ln(R&D Stock/Capital $Stock)_{t-1}]^5$	.002 (.181)	-.033[a] (.015)	-.034[a] (.015)
Year dummies	Yes	Yes	Yes
Firm fixed effects (703)	No	Yes	Yes
No. Observations	12,679	12,679	12,679

[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 equation is estimated by OLS (robust standard errors in brackets). 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 individual Effects	Fixed Effects	Fixed Effects + Dynamics	Fixed Effects + Dynamics (drop SPILLSIC)
Ln(SPILLTECH) $_{t-1}$	.523 (.026)	.343 (.148)	.223 (.129)	0.262 (.113)
Ln(SPILLSIC) $_{t-1}$	-.009 (.012)	.043 (.062)	.044 (.060)	
Ln(R&D Stock) $_{t-1}$	.450 (.023)	.223 (.039)	.065 (.035)	0.067 (0.035)
Ln(Sales) $_{t-1}$	.079 (.021)	.561 (.043)	.273 (.037)	0.274 (0.036)
Ln(Patents) $_{t-1}$			.513 (.019)	0.513 (0.019)
Over-dispersion (alpha)	3.884 (.087)	.412 (.018)	.208 (.013)	0.209 (0.013)
Year dummies	Yes	Yes	Yes	Yes
Firm fixed effects (712)	No	Yes	Yes	Yes
No. Observations	11,024	11,024	11,024	11,024
Log Likelihood	-19,512	-14,413	-13,742	-13,742
Pseudo-R^2	.112	.344	.375	.375

Notes: Estimation is conducted using the Negative Binomial model (robust standard errors in brackets). The estimation period is 1981-1998. A dummy variable is included for observations where lagged patent stock or lagged R&D stock equals zero. Fixed effects in columns (2) through (4) are estimated following Hausman, Hall and Griliches (1984). The results are similar when we use the method in Blundell, Griffith and Van Reenen (1999).

Table 5: Coefficient Estimates for the R&D Equation

Dependent variable ln(R&D)	(1)	(2)	(3)
	No Effects	Fixed Effects	Fixed Effects + Dynamics
Ln(SPILLTECH) $_{t-1}$	.179 (.009)	-.018 (.035)	-.010 (.023)
Ln(SPILLSIC) $_{t-1}$	.317 (.009)	.109 (.020)	.025 (.014)
Ln(Capital) $_{t-1}$	0.119 (0.022)	.216 (.017)	.036 (.013)
Ln(Sales) $_{t-1}$	.703 (.025)	.609 (.021)	.189 (.016)
Ln(R&D) $_{t-1}$			.689 (.014)
Ln(Industry Sales) $_{t}$	.660 (.079)	.143 (.029)	.135 (.022)
Ln(Industry Sales) $_{t-1}$	-.868 (.078)	-.062 (.030)	-.102 (.022)
Year dummies	Yes	Yes	Yes
Firm fixed effects (536)	No	Yes	Yes
No. Observations	8395	8395	8395

Notes: Estimation is by OLS (robust standard errors in brackets). The sample includes only firms which performed R&D continuously in at least two adjacent years. Estimation period is 1981-2001.

Table 6. Theory vs. Empirics

	Partial correlation of:	Theoretical Prediction	Empirical Result	Consistent
$\frac{\partial V^0}{\partial r_\tau}\|_{r0}$	Market value with SPILLTECH	Positive	0.076	yes
$\frac{\partial V^0}{\partial r_m}\|_{r0}$	Market value with SPILLSIC	Negative	-0.039	yes
$\frac{\partial k_0}{\partial r_\tau}\|_{r0}$	Patents with SPILLTECH	Positive	0.223	yes
$\frac{\partial k_0}{\partial r_m}\|_{r0}$	Patents with SPILLSIC	Zero	0	yes
$\frac{\partial r_0}{\partial r_\tau}$	R&D with SPILLTECH	Ambiguous	0	no
$\frac{\partial r_0}{\partial r_m}$	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). Any result which is not significant at the 10% level or better is denoted by "0".

6.4. Extensions

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 to pick up price movements (in later versions we will use industry-specific deflators), so such price effects may be present.

These results should be taken as very preliminary 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).

Table A1 summarizes the results. In the specification without firm fixed effects (column 1), we estimate the output elasticity of own R&D at .045, which is in line with the literature. But we find no effect for $SPILLTECH$, and a negative effect for $SPILLSIC$. However, when we allow for fixed effects the results change dramatically. 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. However, product market rivals R&D also has a significant positive impact on measured productivity. It is not surprising that there is an effect, given the crude adjustment for prices we use.

In the absence of price deflators, we include industry sales variables to pick up demand factors that may be correlated with price-cost margins (column 3). This is our preferred specification. The elasticity on own-R&D is robust to these variables, now estimated at .042. Evaluated at the sample means, this implies a marginal product (gross, private rate of return) of 21 percent. The coefficient on $SPILLTECH$ falls – from .092 to .034 – but remains statistically significant. Evaluated at sample means, an extra dollar of $SPILLTECH$ increases productivity by 1.7 cents. But in this specification the effect of $SPILLSIC$ disappears, which is what we expect if the industry sales variables capture the price effects not controlled for by the output price deflator.

7. 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.

8. References

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Table A1: Coefficient Estimates for the Production Function

Dependent variable Ln(Sales)	(1)	(2)	(3)
	No Effects	Fixed Effects	Fixed Effects
Ln(SPILLTECH) $_{t-1}$	-.0005 (.035)	.092 (.018)	.034 (.017)
Ln(SPILLSIC) $_{t-1}$	-.014 (.003)	.023 (.011)	.002 (.009)
Ln(Capital) $_{t-1}$	.292 (.006)	.183 (.009)	.180 (.009)
Ln(Labour) $_{t-1}$	.645 (.008)	.641 (.011)	.632 (.011)
Ln(R&D Stock) $_{t-1}$	.045 (.023)	.056 (.005)	.042 (.005)
Ln(Industry Sales) $_{t}$			.186 (.021)
Ln(Industry Sales) $_{t-1}$			-.031 (.021)
Year dummies	Yes	Yes	Yes
Firm fixed effects (703)	No	Yes	Yes
No. Observations	12,663	12,663	12,663

Notes: Estimation is by OLS (robust standard errors in brackets). A dummy variable for observations where lagged R&D equals to zero is included. Estimation period is 1981-2001.