Technology sourcing by UK manufacturing firms: an empirical analysis using firm-level patent data*

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Abstract

This paper examines whether UK firms that locate their R&D activity in the USA benefit more than other UK firms from knowledge spillovers originating from US R&D. Patent data provides a firm-level measure of the location of innovative activity, which enables the identification of knowledge spillovers associated with "technology sourcing". We find evidence for such spillovers, although the data do not currently allow a clear differentiation between technology sourcing and an absorptive capacity effect. Future research may be able to clarify these issues by using an enlarged dataset and exploiting more of the information provided by the patent data. In particular the use of citations data to create a more precise measure of the spillover pool available to each firm provides a potentially fruitful avenue of research.

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1. Introduction

This paper examines whether UK firms that locate innovative activity in the USA benefit more than other UK firms from knowledge spillovers originating from US R&D. Several recent studies have found that gaining access to new technology is an increasingly important reason for firms to locate R&D abroad [For example Serapio and Dalton (1999) and Kuemmerle (1999).], and that, as the technological leader in many industries, the USA is one the principal recipients of this kind of R&D investment by subsidiaries of foreign firms. Evidence that knowledge spillovers are partly geographical in scope [See for example Jaffe, Trajtenberg and Henderson (1993) or Keller (2001).] provides a rationale for such 'technology sourcing' behaviour in order to overcome geographical barriers. In this context the flow of knowledge from foreign R&D subsidiaries of domestic multinationals back to the domestic economy may play an important role in the diffusion of new technologies and productivity growth. This has implications for both firm strategy and government policy. For example, an R&D tax credit that encourages firms to repatriate R&D activity may be partly counterproductive.

This paper has two main advantages over most previous studies of international knowledge spillovers. Firstly it uses a firm-level panel data set, which allows for better modelling of heterogeneity between firms than industry or country-level studies. Secondly it uses information from patent data on the location of inventors to create a geographical measure of firms' innovative activity. This provides a specific channel through which to identify international knowledge spillovers associated with technology sourcing.

The structure of this paper is as follows. Section 2 discusses previous literature on spillovers, and puts this research in context. Section 3 presents the basic model and Section 4 describes the data. Section 5 explains our methodology and presents the empirical results, and a final section concludes.

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 analysed at the country, industry, firm and establishment level using a wide variety of techniques and data types [For surveys ee Griliches (1992), Mairesse (1995), and Hall (1996)]. 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 [For recent surveys of empirical studies see Keller (2001) and Cincera and Van Pottelsberghe de la Potterie (2001)].

There are several ways in which one firm's innovative activity can affect aspects of 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 [For example Jaffe (1986) and more recently Harhoff (2000)] which may be hard to distinguish from any 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, although other performance measures such as patenting have also been used as dependent variables. 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 eloquently 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 recognise 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.

The literature contains many different approaches to constructing this 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 neighbours 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 beacuse 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.

2.1. International spillovers

The topic of international spillovers has received a great deal of attention over recent years [For recent surveys of empirical studies see Keller (2001) and Cincera and Van Pottelsberghe de la Potterie (2001)]. The theoretical literature has considered the role of technological externalities in generating endogenous growth and determining the pattern of trade. In some of these models externalities can have important effects on the equilibrium pattern of trade and production. For example, if spillovers are localised or mostly intra-national in scope, there can be multiple equilibria, and government policies can permanently affect comparative advantage by promoting domestic producers in high-technology sectors. This is very different to the traditional Hecksher-Ohlin framework where equilibrium is determined by exogenous factor endowments. These kinds of theoretical developments have made estimating the determinants, scope and size of international spillovers a major goal of empirical research.

In particular many papers have attempted to evaluate the importance of a particular mechanism, such as trade or foreign direct investment, as a channel for technology diffusion. An often-cited early empirical investigation is Coe and Helpman (1995). They undertake pooled cointegrated regressions of country-level log TFP on domestic and foreign knowledge stocks, where the foreign R&D capital stock is constructed using import-weighted sums of trading partners' cumulative R&D spending. They find that foreign R&D is an important source of domestic TFP growth, the more so the more open the economy is to trade. Several authors have questioned Coe and Helpman's methodology, suggesting amongst other things that the spillovers they pick up are mostly 'rent spillovers', and that their import weightings may be proxying for other features of an economy such as openness to foreign competition. The relevance of their weightings is certainly questioned by Keller (1996) who finds higher coefficients on foreign R&D using random trade weightings.

Branstetter (1996) casts doubt on the usefulness of studies that use such high levels of aggregation and so do not account for technological heterogeneity between firms. In particular, without some firm-level measure of proximity, either geographical or technological, any positive results may be due to common demand or input price shocks, or a common time trend, rather than actual spillovers. He uses firm-level panel data from the US and Japan to estimate the relative importance of international and intranational knowledge spillovers. He constructs domestic and foreign spillover pools using the knowledge-weighting technique developed by Jaffe (1986), and estimates a patent equation and a production function. He concludes that knowledge spillovers are mainly intranational in scope, although this conclusion may be partly a result of the choice of the US and Japan, both large countries at the forefront of technological innovation. Keller (2001) does a geographic analysis of industry-level R&D spillovers from the G5 countries to 9 other OECD countries. He finds that spillovers from R&D do get weaker with distance, becoming half as strong over about 1,200 kilometres. However, he also finds that the pool of knowledge became substantially more global between 1970-82 and 1983-95.

If, as it seems, spillovers from foreign innovation are important and beneficial, a natural question from a policy point of view is how they can be enhanced or used to best effect. As discussed above, many papers investigate whether particular activities, mainly trade or FDI, are particularly associated with knowledge spillovers, often but not always coming to a positive conclusion. Griffith, Redding and Van Reenen (2001) investigate whether domestic R&D, in addition to its conventional role of stimulating innovation, also enhances knowledge spillovers by improving the ability of firms to learn about innovations at the leading edge of technology. This corresponds to the notion of "absorptive capacity" associated with Cohen and Levinthal (1990). Using a panel of industries across twelve OECD countries they find that domestic R&D does indeed facilitate technology 'catch-up', although they only find a small impact of trade on productivity growth. The results suggest that estimates of the return to R&D that are based on the

USA could be too low when applied to other countries that operate within the technological frontier.

One influential avenue of recent research uses the rich source of data found in patent citations to trace the path of knowledge flows. This can be seen as an attempt to look directly at the process of knowledge diffusion, as opposed to the "reduced form" evidence provided by productivity regressions. Jaffe et al (1993), and Jaffe and Trajtenberg (1998), find that even after controlling for other factors, patents whose inventors reside in the same country are typically 30% to 80% more likely to cite each other than inventors from other countries, and that these citations tend to come sooner. They also find that localisation does fade over time, but only very slowly. Branstetter (2000) uses patent citations to show that foreign direct investment (FDI) between Japan and the USA increases knowledge flows. Using similar techniques, Singh (2002) investigates the role of multinational subsidiaries in knowledge diffusion. He finds that the extent of knowledge flows from domestic firms to multinational subsidiaries seems to be much stronger than that in the opposite direction, while Criscuolo (2002) also uses citations and finds that multinationals act as a channel for the transmission of knowledge developed abroad to other home country firms.

2.2. Technology sourcing

These last two studies come close to addressing the issue of technology sourcing. Several recent papers have suggested that access to new technology is an increasingly important motivation for firms locating R&D activity abroad. Serapio and

Dalton (1999) argue that much of the globalisation of innovative activity has involved foreign firms locating R&D activities in the USA in order to benefit from technology sourcing at the leading edge of technological innovation: "Foreign parent companies, particularly in the drugs/biotechnology and electronics industries, have established or acquired foreign R&D laboratories in the US in order to gain access to science and technology, and enhance their global capabilities for technology development and innovation." This interpretation of foreign R&D investment is in contrast with earlier interpretations which focussed on the importance of adapting technologies developed at home to the conditions of the foreign market (Le Bas and Sierra, 2002).

Serapio and Dalton document the fact that UK firms are a particularly significant part of this development, with the third highest R&D expenditures in the USA in 1996 of all foreign countries. Bloom and Griffith (2001) have documented the internationalisation of UK R&D, both in terms of R&D that is performed in the UK but funded from abroad, and UK firms doing more of their R&D overseas. They find that UK R&D is more internationalised than in other G5 countries and is becoming more so at a faster rate.

Much of the research discussed above, especially the work by Jaffe and others on patent citations, suggests that technology sourcing may be a plausible mechanism for reducing the geographical localisation of knowledge spillovers. However, we are aware of no studies that attempt to find empirical evidence for technology sourcing in terms of its effects on productivity. We believe that the information on inventor location used in this study provides an ideal channel for identifying knowledge spillovers associated with technology sourcing.

3. The basic model

The basic approach follows Griliches (1979) and many subsequent papers by including measures of the external knowledge stock available to the firm in a firm-level production function. Thus we assume that the firm's value added can be written as follows

$$Y_{it} = Q(X_{it}, G_{it}) \tag{3.1}$$

where Y_{it} is real value added for firm i in year t, X_{it} is a vector of the firm's own inputs including labour, capital and the firm's own knowledge stock accumulated by doing R&D, and G_{it} is the external knowledge stock available to the firm. As discussed above, the key assumption with respect to identifying spillovers is how to define G_{it}. Because we want to identify geographical aspects of spillovers we assume that G_{it} is composed of a domestic and a foreign component, and do not restrict the response of the firm's value added to each component to be the same.

$$G_{it} = (D_{it}, F_{it}) \tag{3.2}$$

$$Y_{it} = Q(X_{it}, D_{it}, F_{it}) \tag{3.3}$$

The key innovation is that we allow the elasticity of value added with respect to the foreign and domestic external knowledge stocks to depend on firm-specific characteristics, namely a measure of "absorptive capacity" and a measure of the geographical location of the firm's innovative activity. So we have

$$\frac{\partial Y_{it}}{\partial D_{it}}\frac{D_{it}}{Y_{it}} = d(P_i, W_i^D) \tag{3.4}$$

$$\frac{\partial Y_{it}}{\partial F_{it}}\frac{F_{it}}{Y_{it}} = f(P_i, W_i^F) \tag{3.5}$$

where P_i is some measure of absorptive capacity, and W_i^D and W_i^F are measures of the amount of the firm's innovative activity that is located at home or abroad respectively. Allowing the response of value added to the spillover pool to vary with the firm's absorptive capacity is a fairly standard extension, and as will become clear later on, it may be an important control to prevent any possibly spurious effect of the location measures. One plausible restriction is that a firm's absorptive capacity affects its ability to pick up domestic or foreign spillovers equally.

$$\frac{\partial d}{\partial P_i} = \frac{\partial f}{\partial P_i} \tag{3.6}$$

It truns out that this restriction is not rejected by our data, and we impose it in our preferred specification. However, it is only a simplifying restriction and the main results are robust to relaxing it.

The most important aspect of our basic model is that the location measures allow identification of knowledge spillovers associated with technology sourcing in a way that should be less susceptible to the Manski-Griliches critique discussed earlier. While many studies claim identification of knowledge spillovers in this context from a positive response of value added to the external spillover pool, we only infer the existence of spillovers if the magnitude of that response depends positively on a direct proxy for a channel of knowledge transfer. In other words only if

$$\frac{\partial f}{\partial W_i^F} > 0 \tag{3.7}$$

A positive response of value added to the spillover pool could be due to a "correlated effect" if the variables used to define the spillover pool are related to unobserved variables that directly affect value added. Inferring the existence of knowledge spillovers simly from an observed positive response thus depends on the assumption that no such relationship exists. In our approach identification depends only on the much weaker assumption that the nature of the relationship does not depend on our measure of the geographical location of innovative activity.

4. Data

The IFS-Leverhulme database used in this paper is a combination of two datasets. Full details of the matching between the datasets can be found in Bloom and Van Reenen (2000), and the process is sketched in the Appendix at the end of this paper. The first dataset is the NBER patent citations data file which contains computerised records of over two million patents granted in the USA between 1901 and 1999. This is the largest electronic patent data set in the world. The second dataset is the Datastream on-line service which contains accounts of firms listed on the London Stock Exchange over 1968-2000. The initial sample is all firms existing in 1985 with names starting with the letters A-L, plus any of the top 100 UK R&D performers not already included, in order to maximise the number of patents matched to firms. This gives 415 firms.

4.1. Patent data

The intersection of the two datasets gave 266 firms who had taken out at least one patent between 1975 and 1998, categorised by date of application. The reason for restricting our attention to patents applied for after 1975 was partly in order to make the patent information as up to date as possible, and partly because citations data is only available after 1975. While we do not use citations data in this paper, we plan to in the future.

The information that we use from the patent data is the country address of the inventor(s) listed on the patent application. Table 1 lists the inventor's country for the 63,733 patents matched to the 266 firms. The high share of patents invented in the USA is probably partly due to home-country bias from using a US dataset, but also reflects the county's strong innovative performance and the location of many UK firms in the USA. An overall bias towards US based patents should not be a problem as long as it is not different across firms in a way that is related to other firm characteristics.

[Table 1 here]

4.2. Accounts data

The initial sample of 415 firms was cleaned for estimation. This included ensuring that employment observations were available, deleting firms with less than five consecutive observations over 1990 - 2000, and excluding firms for which there were jumps of greater than 150% in any of the key variables (capital, labour, sales). Capital stock was constructed by a perpetual inventory method as in Bloom and Van Reenen (2000). The data does not include intermediate inputs, so value added was constructed as the sum of total employment costs, operating profit, depreciation and total interest charges. Because of UK accounting regulations, most of the firms did not report R&D expenditure before 1989, and so the analysis is restricted to the years 1990-2000. [Even after 1989 when a firm reports zero R&D it is not clear that this corresponds to a true zero, although it is unlikely to perform a large amount of R&D. In the results presented in this paper, a dummy variable was used to denote reported zero R&D expenditure, but the results are not very sensitive to the exact treatment of reported zeros.] An R&D capital stock was constructed using a perpetual inventory method and an assumed 15% rate of obsolescence, but the results are fairly robust to different rates. Spending on R&D is also included in the main labour and capital variables so any estimated returns to R&D are "excess" returns [See Griliches (1979)].

Although these are "UK firms" in the sense that they are listed on the London Stock Exchange, a key feature of the data is that it relates to the firm's global activities. As discussed later this has potentially important consequences for the interpretation of our results. For now we maintain the assumption that, while a firm's innovative activity may be located anywhere in the world, its production activity is located in the UK. We examine the validity of this assumption and the consequences of any violations later on.

4.3. Spillover pool data

The domestic and foreign spillover pools were constructed using the OECD's "Analytical Business Expenditure on R&D" dataset (ANBERD, 2002) on R&D spending by two-digit manufacturing industry (ISIC Revision 3) in the UK and the USA. A stock measure was constructed using a perpetual inventory method and an assumed 15% rate of obsolescence, with a starting year of 1987. Although there are various problems with using industry-level measures as discussed above, this data has the crucial advantage for our purposes that it contains R&D expenditures by geographical location. This would be extremely hard if not impossible to recreate using a weighted sum of other firms' R&D. It also has the advantage of including all R&D carried out in each industry in each country, and not just the R&D of the other sampled firms.

Because the source of identification in our model comes from the way the response of value added to the spillover pool depends on the geographical location of innovative activity, the possibility of spurious "correlation effects" due to a spillover pool constructed at the industry-level should not be a serious problem. However, in order to at least partly control for industry level cyclical effects and shocks not associated with knowledge spillovers, we also include two-digit industry-level value added in our preferred specification. This was taken from the OECD's "Structural Analysis" database (STAN, 2001).

Firms were assigned to a two-digit industry according to where the largest proportion of their sales was classified. Although this inevitably leads to some misclassification of activity, Aghion et al (2002) used the same data and found that for 35% of firms this captured all their sales, and that the median percentage of sales captured by this classification was 90%. Keller (2001) concludes that any bias resulting from such misclassification is likely to be small.

After cleaning as described above and limiting the sample to manufacturing firms we are left with 1774 observations on 194 firms, 142 of which are matched to at least one patent. Table 2 reports summary statistics.

[Table 2 here]

5. Methodology and Results

5.1. Functional form

We consider a Cobb-Douglas production function with constant returns in labour and capital inputs

$$Y_{it} = A_{it} L_{it}^{\alpha} K_{it}^{1-\alpha} R_{it}^{\beta} D_{jt}^{\gamma_1} F_{jt}^{\gamma_2} \tag{5.1}$$

where i indexes a firm, j indexes the firm's two digit industry, and t indexes the year. Y_{it} is real value added, L_{it} is observed labour inputs, K_{it} is a measure of the firm's capital stock, R_{it} is a measure of the firm's own knowledge stock, and D_{jt} and F_{jt} are the R&D stock in the firm's two-digit industry in the UK and the USA respectively. We assume that the elasticities of value added with respect to the external knowledge stocks are a linear function of a firm-specific measure of absorptive capacity and firm-specific measures of the location of innovative activity

$$\gamma_1 = \theta_0 + \theta_1 P_i + \theta_2 W_i^{UK} \tag{5.2}$$

$$\gamma_2 = \phi_0 + \phi_1 P_i + \phi_2 W_i^{US} \tag{5.3}$$

where the restriction embodied in equation (3.6) implies that $\theta_1 = \phi_1$, and a positive estimate of ϕ_2 would provide evidence of knowledge spillovers associated with technology sourcing.

W_i^{UK} and W_i^{US} are constructed as the proportion of the firm's total patents where the inventor is located in the UK or the USA respectively. They are both equal to zero if the firm has no patents. This form for the measure of the geographical location of innovative activity discards two forms of information in the patent data. The first is variation over time, so that the measure represents an average of the location of the firm's innovative activity over the period 1975-1998. The second form of information is the total number of the firm's patents. While this may be relevant information, normalising the location measures to a proportion between zero and one helps to deal with difficulties associated with firm size and differences in propensity to patent across industries.

This form for the location measures motivates the form of the measure of absorptive capacity P_i. This is a firm-specific dummy variable that is equal to one of the firm is matched to at least one patent, and zero if it has no patents at all. Without controlling for absorptive capacity in this way, it would not be possible to determine to what extent a positive effect of W_i^{UK} and W_i^{US} on γ_1 and γ_2 was due to the fact that the firm was a patenter at all rather than due to geographical location of innovative activity. However, this raises a problem of multicollinearity. When P_i is equal to zero, W_i^{UK} and W_i^{US} are also zero because the firm has no patents. If "abroad" is taken to be the whole of the rest of the world, then when $P_i = 1$ we must have $W_i^D + W_i^F = 1$. Because we use only the USA this will not generally be exactly true, but as reported in Table 3 the median value of $W_i^{UK} + W_i^{US}$ in our sample of 194 firms is 0.95, so the problem remains. The key point is that to identify technology sourcing effects, there must be enough actual variation in the data to enable us to differentiate between the information in W_i^{UK} and W_i^{US} that relates to geographical location of innovation, and that information which captures the fact that the firm does any innovation at all. As we shall see this problem plays a key role in the interpretation of our results.

[Table 3 here]

We estimate this functional form in logs

$$(y_{it} - k_{it}) = \alpha(l_{it} - k_{it}) + \beta r_{it} + \gamma_1 d_{jt} + \gamma_2 f_{jt} + a_{it}. \tag{5.4}$$

where variables in lower case denote the natural logarythm. Once all the interactions with patenting and geographical location are included, as well as industry value added in the UK and the USA, the full specification becomes

$$
\begin{aligned}
(y_{it}-k_{it}) &= \alpha(l_{it}-k_{it})+\beta r_{it}+\theta_0 d_{jt}+\phi_0 f_{jt}+\theta_2 W_i^{UK} d_{jt}+\phi_2 W_i^{US} f_{jt} \\
&\quad +\theta_1 P_i(d_{jt}+f_{jt})+\delta_1 v_{jt}^{UK}+\delta_2 v_{jt}^{US}+W_i^{UK}+W_i^{US}+P_i+a_{it}
\end{aligned} \tag{5.5}
$$

5.2. Estimation

We assume that the residual productivity term takes the form

$$
a_{it} = t_t + \eta_i + u_{it}. \tag{5.6}
$$

where the year dummies control for common macro effects and the firm effect and stochastic productivity shock may be correlated with the regressors. We allow for arbitrary heteroskedasticity and possible serial correlation in the stochastic productivity shock. We include industry dummies in all regressions. We estimate using Systems-GMM [See Blundell and Bond (1999) for an exposition and a production function example], where the information from the levels equation helps to alleviate the weak instruments problem associated with first-difference GMM when series are persistent. The additional moment conditions take the form

$$
E[\Delta x_{i,t-s}(\eta_i + u_{it})]. = 0 \tag{5.7}
$$

for $s = 1$ when $u_{it} \sim AR(0)$ and for $s = 2$ when $u_{it} \sim AR(1)$, where x_{it} indicates the regressors being instrumented. This requires the first moments of x_{it} to be time-invariant, conditional on common year dummies.

We assume that all firm-level variables are endogenous, while all industry-level variables are treated as strictly exogenous. The results are robust to lagging the industry-level variables by one period, in which case they can be treated as predetermined. We instrument firm-level variables in the differenced equation with their levels lagged from two to five times inclusive, and in the levels equation by their first-differences lagged once, as well as by all time and industry dummies and all exogenous variables.

5.3. Empirical Results

Table 4 presents results for the basic production function and the basic spillover and value added terms. Column (1) is OLS without imposing constant returns to scale in labour and capital, while column (2) does impose constant returns. [Nickell- type justification for CRS? CRS rejected in OLS but not GMM specifications]. Column (3) is the basic production function using Systems-GMM. The coefficient on capital is lower than in the OLS case. This is quite a common feature of GMM estimation of production functions, and may reflect measurement error in the capital stock [See Griliches and Mairesse (1995) for a discussion]. The estimated elasticity with respect to own R&D corresponds to a median private excess rate of return to R&D of about 20%, which is similar to that found in other studies [See Griliches (1992)]. Tests are presented for first and second order serial correlation in the first-differenced residuals, with robust p values in brackets. Thus the negative first order serial correlation is as expected for first-differenced residuals, and the absence of second order correlation in the differenced residuals suggests that the original stochastic productivity shock is not serially correlated. This justifies the use of twice lagged instruments in the difference equation and once lagged instruments in the levels equation. A Sargan test of overidentifying restrictions is not significant. Columns (4) and (5) introduce the main industry level spillover terms and value added terms respectively. The main spillover terms do not enter significantly, and the coefficient on the UK term becomes close to zero when value added is included. Both value added terms are positive and significant at the 10% level, suggesting that they are indeed controlling for industry level effects not associated with knowledge spillovers.

Table 5 presents the key results. Column (1) is the same as Column (5) of Table 4 for ease of comparison. Column (2) introduces the geographical location interactions. The interaction with the US location measure is positive and significant at the 1% level, suggesting the existence of knowledge spillovers associated with technology sourcing from the USA. The UK interaction is smaller and not significant. This is not very surprising for a sample of UK firms, in that the marginal effect of locating innovative activity in the UK on the firm's ability to benefit from spillovers from UK R&D is likely to be smaller than in the US case. The significant negative effect of the location measures W_i^{UK} and W_i^{US} themselves is only observed conditonal on the inclusion of the interaction terms, and they both enter positively when the interactions are not included. The median marginal effect of W_i^{UK} and W_i^{US} on value added remains positive.

As discussed earlier, just looking at the evidence presented in Column (2) does not enable us to distinguish with certainty between a technology sourcing interpretation and an absorptive capacity interpretation. As Column (3) shows, the measure of absorptive capacity on its own does seem to have some explanatory power. However, when the location and the absorptive capacity interactions are all included in Column (4) none of them enters significantly, although a Wald test reveals that they are jointly significant at the 10% level. This is the collinearity issue referred to above; the data do not contain enough variation to distinguish clearly between a technology sourcing and an absorptive capacity interpretation.

However, closer inspection of the point estimates reveals, that while the coefficients on the location interactions are not greatly reduced between columns (2) and (4), the coefficient on the absorptive capacity interaction is now very close to zero. This suggests that in a contest between the two interpretations, the data appears to favour technology sourcing, but not unambiguously so.

A further issue relates to the fact that the data represents firms' global activity. Although we have been assuming that production activity is located in the UK, this is not completely true in practice. It is possible that the location measure W_i^{US} is not only proxying for the location of innovative activity, but also for the location of production. In other words, firms with innovative activity in the USA are likely also to have productive activity located there. If this is the case, then we may not only picking up international spillovers but also domestic spillovers within the USA, with all the ensuing identification issues that were discussed earlier.

We attempt to control for this by using the separate reporting of domestic employment to total employment. 118 out of 194 firms report domestic employment separately to total employment at least once during 1990-2000. For those that do not report separately we assume that all employment is domestic. Of those 118 firms, 54 report total employment greater than domestic employment at least once. We drop these firms from the sample and re-estimate our model on the remaining 140 firms, which we expect to have little or no foreign production activity. Table 6 presents the same specifications as table 5 except now only for the 140 firms. The results are very similar, suggesting that the initial results were not primarily driven by the location of firms' production activities. Future investigation of this issue might attempt to control for the country location of sales, for which there exists some limited data.

6. Summary and Conclusions

The results presented in this paper provide some evidence for the existence of knowledge spillovers associated with technology sourcing. Using the current data it is difficult to distinguish clearly between an absorptive capacity effect and technology sourcing, but it seems likely that the location information provided by patent data does have some explanatory power in explaining the pattern of international knowledge spillovers. Future research may be able to clarify these issues by using an enlarged dataset and exploiting more of the information provided by the patent data. In particular the use of citations data to create a more precise measure of the spillover pool available to each firm provides a potentially fruitful avenue of research.

7. References

Aghion, P., Bloom, N., Blundell, R., Griffith, R. and Howitt, P. (2002), "Competition and innovation: An inverted U relationship", Institute for Fiscal Studies Working Paper No. W02/04

Bernstein, J. I. and Nadiri, M. I. (1989), "Research and development and intra-industry spillovers: An empirical application of dynamic duality", Review of Economic Studies 56, pp 249-269

Bloom, N. and Griffith, R. (2001), "The internationalisation of R&D", Fiscal Studies 22 (3), pp 337-355

Bloom, N. and Van Reenen, J. (2000), "Real options, patents, productivity and market value: Evidence from a panel of British firms", Institute for Fiscal Studies Working Paper No. W00/21

Blundell, R. and Bond, S. (1999), "GMM estimation with persistent panel data: An application to production functions", Institute for Fiscal Studies Working Paper No. W99/4

Branstetter, L. (1996), "Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the U.S. and Japan", NBER Working Paper No. 5800

Cincera, M. and Van Pottelsberghe da la Potterie, B. (2001), "International R&D spillovers: a survey", Cahiers Economiques de Bruxelles, 169, pp 3-32

Cohen, W. M. and Levinthal, D. A. (1990), “The implications of spillovers for R&D investment and welfare: A new perspective”, Administrative Science Quarterly 35, pp 128-152

Criscuolo, P. (2002), "Reverse technology transfer", Unpublished Paper, University of Sussex

Griffith, R., Redding, S. and Van Reenen, J. (2001), “Mapping the two faces of R&D: Productivity growth in a panel of OECD industries”, Institute For Fiscal Studies Working Paper W02/00

Griliches, Z. (1979), “Issues in assessing the contribution of research and development to productivity growth”, Bell Journal of Economics 10 (1), pp 92-1167

Griliches, Z. (1992), “The search for R&D spillovers”, Scandinavian Journal of Economics 94, supplement, pp S29-S47

Griliches, Z. (1994), “Productivity, R&D, and the data constraint”, American Economic Review 84, (1), pp 1-23

Griliches, Z. (1996), “R&D and productivity: The unfinished business”, in Z.Griliches (1998), R&D and Productivity: The Econometric Evidence, The University of Chicago Press, Chicago and London

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

Griliches, Z. and Mairesse, J. (1995), “Production functions: The search for identification", NBER Working Paper No. 5067

Grossman, G. M. and Helpman, E. (1991), Innovation and Growth in the Global Economy, MIT Press, Cambridge, Mass.

Hall, B. H. (1996), "The private and social returns to R&D", in Technology, R&D and the Economy, ed. B. Smith and C. Barfield, Brookings Institution and AEI, Washington D.C., pp 140-162

Hall, B. and Mairesse, J. (1996), "Estimating the productivity of research and development: An exploration of GMM methods using data on French and United States manufacturing firms", NBER Working Paper No. 5501

Harhoff, D. (2000), "R&D spillovers, technological proximity, and productivity growth – Evidence from German panel data", Schmalenbach Business Review 52, pp 238-260

Jaffe, A. (1986), "Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits and market value", American Economic Review 76, pp 984-1001

Jaffe, A. and Trajtenberg, M. (1998), "International knowledge flows: Evidence from patent citations", NBER Working Paper No. 6507

Jaffe, A., Trajtenberg, M. and Henderson, R. (1993), "Geographic localisation of knowledge spillovers as evidenced by patent citations", Quarterly Journal of Economics 108 (3), pp 577-598

Keller, W. (1996), "Are international R&D spillovers trade-related? Analyzing spillovers among randomly-matched trade partners", SSRI Working Paper No. 9607, University of Wisconsin, Madison

Kuemmerle, W. (1999), "The drivers of foreign direct invetsment into research and development: an empirical investigation", Research Policy, 30 (1), 1-24

Keller, W. (2001), "Geographic localization of international technology diffusion", CEPR Discussion Paper No. 2706

LeBas, C. and Sierra, C. (2002), "Location versus home country advantages in R&D activities", Research Policy, 31, pp 589-609

Mairesse, J. (1995), "R&D productivity: A survey of the econometric literature", Paper presented at the CEPR workshop on R&D spillovers, Lausanne, Jan. 27/28 1995

Manski, C. (1991), "Identification of endogenous social effects: The reflection problem", Review of Economic Studies 60 (3), pp 531-42

Nickell, S. (1996), "Competition and corporate performance", Journal of Political Economy 104

OECD (2001), "Structural Analysis Data Base", Paris

OECD (2002), "Analytical Business Enterprise Research and Development", Paris

Reinganum, J. (1989), "The timing of innovation: Research, Development and Diffusion", in R. Schmalensee and R. D. Willig (eds), Handbook of Industrial

Organization, North-Holland, Amsterdam, Vol. 1, pp 849-908

Scherer, F. M. (1982), "Interindustry technology flows and productivity growth", Review of Economics and Statistics LXIV, pp 627-634

Serapio, M. G. Jr. and Dalton, D. H. (1999), "Globalization of industrial R&D: an examination of foreign direct investments in R&D in the United States", Research Policy 28, pp 303-316

Singh, J. (2002), "Knowledge diffusion and the role of multinational subsidiaries", Unpublished Paper, Harvard University

Spence, A. M. (1984), "Cost reduction, competition and industry performance", Econometrica 52, pp 101-121

Trajtenberg, M. (1990), Economic Analysis of Product Innovation: The Case of CT Scanners, Harvard University Press, Cambridge, Mass.

8. Data Appendix

The full data matching process can be found in Bloom and Van Reenen (2000), but the main aspects are sketched here. From the population of public firms quoted on the London Stock Exchange, a random sample of all companies whose names began with the letters 'A' through 'L' were selected. Also selected were the top 100 R&D performing firms in the UK in order to maximise the number of patents that could be matched. For all of these 415 firms Who Owns Whom 1985 was used to manually match each patenting subsidiary to their parent companies.

This process was subsequently checked for all large subsidiaries and outliers using the Internet. Being a manual matching process, the matching accuracy appears to be quite good, and is certainly substantially greater than a computerised flexible string search. In direct comparisons this uncovered only about 10% of the matches found manually.

Table 1: Country of inventor

Country of Inventor	Number of Patents	% Share
USA	28,731	45.1
Japan	4,411	6.9
Germany	2,481	3.9
France	1,457	2.3
UK	19,745	31.0
Other	6,908	10.8
Total	63,733	100

- 266 firms

Table 5: Interactions results

	(1)	(2)	(3)	(4)
Dependent variable	$\ln (VA/K)_{it}$	$\ln (VA/K)_{it}$	$\ln (VA/K)_{it}$	$\ln (VA/K)_{it}$
$\ln (L/K)_{it}$	0.826 ***	0.832 ***	0.812 ***	0.826 ***
	(0.054)	(0.051)	(0.053)	(0.049)
$\ln (R\&D)_{it}$	0.031 **	0.027 *	0.030 *	0.030 *
	(0.015)	(0.017)	(0.017)	(0.017)
$\ln (UK\ R\&D)_{jt}$	0.013	0.039	-0.007	0.043
	(0.095)	(0.096)	(0.095)	(0.103)
$\ln (US\ R\&D)_{jt}$	0.018	-0.067	-0.005	-0.068
	(0.047)	(0.050)	(0.045)	(0.054)
$\ln (UK\ Value\ Added)_{jt}$	0.169 *	0.190 **	0.160 *	0.167 *
	(0.095)	(0.092)	(0.094)	(0.088)
$\ln (US\ Value\ Added)_{jt}$	0.147 *	0.126 *	0.140 *	0.139 *
	(0.076)	(0.074)	(0.072)	(0.073)
$W_i^{UK} * \ln (UK\ R\&D)_{jt}$		0.067		0.049
		(0.045)		(0.070)
$W_i^{US} * \ln (US\ R\&D)_{jt}$		0.097 ***		0.080
		(0.037)		(0.065)
$P_i * \ln (UK + US\ R\&D)_{jt}$			0.030 **	0.005
			(0.014)	(0.028)
W_i^{UK}		-0.688 *		-0.365
		(0.416)		(0.646)
W_i^{US}		-0.875 *		-0.548
		(0.358)		(0.610)
P_i			-0.541 **	-0.278
			(0.231)	(0.462)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
1st order serial correlation	-2.822	-2.802	-2.792	-2.817
	(0.005)	(0.005)	(0.005)	(0.005)
2nd order serial correlation	-0.877	-0.773	-0.815	-0.819
	(0.380)	(0.440)	(0.415)	(0.413)
Sargan	82.63	77.57	81.36	77.27
	(0.310)	(0.460)	(0.345)	(0.470)

- 1774 observations, 194 firms, 1990-2000
- one-step robust standard errors in brackets, except for tests where p values are in brackets.
- All three interactions just jointly significant in (4), (p = 0.07)

Table 4: Basic production function

	(1) OLS	(2) CRS, OLS	(3) CRS, GMM	(4) CRS, GMM	(5) CRS, GMM
Dependent Variable	ln (VA) $_{it}$	ln (VA/K) $_{it}$	ln (VA/K) $_{it}$	ln (VA/K) $_{it}$	ln (VA/K) $_{it}$
ln (L) $_{it}$	0.644 ***	0.697 ***	0.833 ***	0.832 ***	0.826 ***
	(0.018)	(0.015)	(0.054)	(0.054)	(0.054)
ln (K) $_{it}$	0.297 ***	0.303	0.167	0.168	0.174
	(0.014)				
ln (R&D) $_{it}$	0.048 ***	0.015 ***	0.033 **	0.032 **	0.031 **
	(0.007)	(0.003)	(0.015)	(0.015)	(0.015)
ln (UK R&D) $_{jt}$				0.108	0.013
				(0.094)	(0.095)
ln (US R&D) $_{jt}$				-0.007	0.018
				(0.042)	(0.047)
ln (UK Value Added) $_{jt}$					0.169 *
					(0.095)
ln (US Value Added) $_{jt}$					0.147 *
					(0.076)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
1st order serial correlation	_	_	-2.796	-2.844	-2.822
			(0.005)	(0.005)	(0.005)
2nd order serial correlation	_	_	-0.864	-0.827	-0.877
			(0.387)	(0.408)	(0.380)
Sargan	_	_	77.09	78.98	82.63
			(0.476)	(0.416)	(0.310)

- 1774 observations, 194 firms, 1990-2000
- in columns (3), (4) and (5) firm-level variables assumed endogenous and industry level variables assumed strictly exogenous
- endogenous variables are instrumented by levels lagged from two to five times in the differences equation and differences lagged once in the levels equation, as well as by all exogenous variables and year and industry dummies
- one-step robust standard errors in brackets, except for tests where p values are in brackets.

Table 3: Summary Statistics

	Mean	Median	Standard Deviation	Min	Max
All 194 firms:					
Observations	9.1	10	1.8	5	11
Employees	10,850	1,699	28,780	31	308,000
Value added (£m)	366	46	938	1.3	9,222
Capital stock (£m)	573	55	1,635	1.1	14,500
R&D expenditure (£m)	26	0.2	119	0	1,650
UK industry R&D (£m)	560	399	711	22	3,078
US industry R&D ($m)	6,278	3,339	6,534	244	23,929
142 patenters only:					
Total patent applications	248	55	623	1	5590
W_i^{UK}	0.31	0.24	0.33	0	1
W_i^{US}	0.51	0.50	0.36	0	1
$W_i^{UK} + W_i^{US}$	0.83	0.95	0.26	0	1

- All monetary amounts are in 1995 currency
- Value added is constructed as the sum of total employment costs, operating profit, depreciation and interest payments
- Capital stock is constructed using a perpetual inventory method
- Patenters are firms matched to at least one patent

Table 6: Results for the 140 'domestic' firms

	(1)	(2)	(3)	(4)
Dependent variable	ln (VA/K) $_{it}$	ln (VA/K) $_{it}$	ln (VA/K) $_{it}$	ln (VA/K) $_{it}$
ln (L/K) $_{it}$	0.748 ***	0.752 ***	0.728 ***	0.754 ***
	(0.058)	(0.058)	(0.060)	(0.054)
ln (R&D) $_{it}$	0.041 **	0.035 *	0.039 **	0.035 *
	(0.017)	(0.018)	(0.019)	(0.018)
ln (UK R&D) $_{jt}$	0.040	0.069	0.017	0.083
	(0.119)	(0.120)	(0.121)	(0.124)
ln (US R&D) $_{jt}$	0.026	-0.057	0.005	-0.073
	(0.053)	(0.056)	(0.051)	(0.061)
ln (UK Value Added) $_{jt}$	0.280 *	0.313 **	0.279 *	0.298 **
	(0.152)	(0.147)	(0.152)	(0.143)
ln (US Value Added) $_{jt}$	0.139	0.106	0.131	0.112
	(0.115)	(0.111)	(0.112)	(0.111)
W_i^{UK} *** ln (UK R&D) $_{jt}$**		0.082		0.072
		(0.074)		(0.098)
W_i^{US} *** ln (US R&D) $_{jt}$**		0.093 **		0.106
		(0.041)		(0.078)
P_i *** ln (UK + US R&D) $_{jt}$**			0.027 *	-0.003
			(0.016)	(0.033)
W_i^{UK}		-0.855		-0.589
		(0.713)		(0.909)
W_i^{US}		-0.385 **		-0.764
		(0.358)		(0.708)
P_i			-0.489 *	-0.133
			(0.260)	(0.529)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
1st order serial correlation	-2.822	-2.825	-2.795	-2.840
	(0.005)	(0.005)	(0.005)	(0.005)
2nd order serial correlation	-0.877	-0.892	-0.942	-0.915
	(0.380)	(0.440)	(0.346)	(0.360)
Sargan	82.63	76.51	76.24	74.23
	(0.310)	(0.494)	(0.503)	(0.568)

- 1282 observations, 140 firms, 1990-2000