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How Special Is the Special Relationship? Using the Impact of U.S. R&D Spillovers on U.K. Firms as a Test of Technology Sourcing

By RACHEL GRIFFITH, RUPERT HARRISON, AND JOHN VAN REENEN*

There is a consensus among economists and policymakers that an important part of global economic growth arises from the transfer of ideas from the leading-edge countries to those behind the technological frontier. The mechanisms underlying this technology transfer are poorly understood, however, and microeconometric evidence on the quantitative importance of the international spillover process remains thin.[1] In addition, the firm-level evidence on spillovers that does exist tends to be from single countries, and the bulk of these single-country studies are from the United States (US), which, as technological leader in most industries, probably has least to gain from other countries' innovative efforts.

Case studies and the business press have long emphasized the importance of "technology sourcing" as a method of gaining access to foreign knowledge, and several recent studies have suggested that this is an increasingly important motivation for locating R&D abroad.[2] Under this view, firms can tap into leading-edge knowledge by setting up R&D labs abroad to "listen in" on new ideas and use these to improve productivity. The main contribution of our paper is to provide rigorous evidence for technology sourcing from the US by exploiting firm-level panel data from the United Kingdom (UK). UK firms offer a particularly good testing ground for this hypothesis because the UK is both less technologically advanced than the US and has historically close linkages to US-based inventors.[3] For example, in 1993, near the beginning of our sample, affiliates of UK firms located in the US spent \$2.2 billion on R&D, equivalent to 14 percent of total business R&D in the UK. The same percentages for Japan and Germany were 3 percent and 8 percent, respectively.[4] We examine whether the US R&D stock (conditional on UK R&D) had a stronger impact on the total factor productivity (TFP) of UK firms that had more of their inventors located in the US than on other UK firms. We use the pre-1990 location patterns of UK firms, as revealed in individual firms' patent statistics, to mitigate the endogeneity problem arising from the fact that UK firms may choose to locate R&D in the US in response to the 1990s technology boom.[5]

* Griffith: Institute for Fiscal Studies, 7 Ridgmount Street, London, WC1E 7AE (e-mail: rgriffith@ifs.org.uk); Harrison: Institute for Fiscal Studies, 7 Ridgmount Street, London, WC1E 7AE (e-mail: rharrison@ifs.org.uk); Van Reenen: Centre for Economic Performance, London School of Economics, Houghton Street, London, WC2A 2AE (e-mail: J.Vanreenen@lse.ac.uk). We would like to thank Nick Bloom, Steve Bond, Lee Bransetter, Michele Cincera, Bronwyn Hall, Wolfgang Keller, John Sutton, Manuel Trajtenberg, Andrew Wykoff, three anonymous referees, and participants at seminars at IFS, LSE, University of Madrid, National Bureau of Economic Research, World Intellectual Property Organization, Swansea University, and Tilburg University for helpful comments. Financial support for this project was provided by the Economic and Social Research Council through the Centre for the Microeconomic Analysis of Fiscal Policy at the IFS, the Centre for Economic Performance, and the Advanced Institute Management Initiative. The data were developed with funding from the Leverhulme Trust.

[1] See Wolfgang Keller (2004) for a recent survey.

[2] See, for example, Maximilian von Zedtwitz and Oliver Gassman (2002) and Manuel Serapio and Donald Dalton (1999), and the references therein.

[3] In the "market sector" (i.e., excluding health, education, and public administration) labor productivity was about 40 percent higher in the US than in the UK in 1999 (US TFP was about 20 percent higher).

[4] In 1997, of the seven largest foreign research centres in the US, five were owned by UK companies (Serapio and Dalton, 1999). In our data, more than one-third of the patents granted to UK firms and registered at the US Patent Office had their lead inventors located in the US.

[5] R&D intensity by business enterprises in the US (Organisation for Economic Cooperation and Development

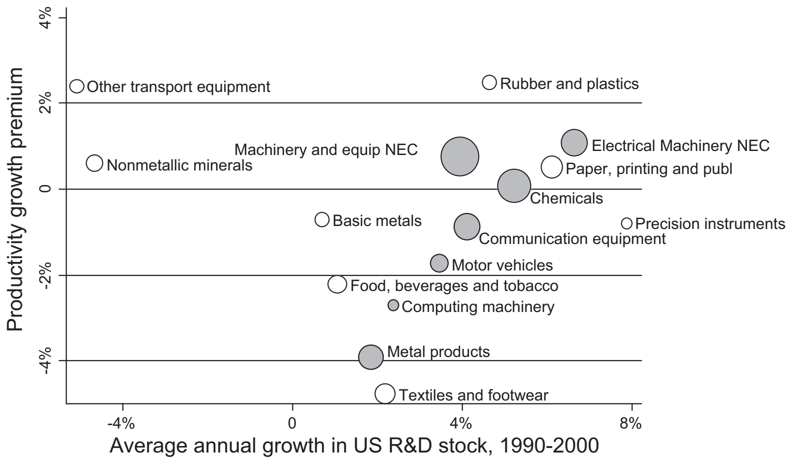

FIGURE 1. US R&D GROWTH AND "PRODUCTIVITY GROWTH PREMIUM" FOR UK FIRMS WITH A HIGH PROPORTION OF US INVENTORS

Notes: The vertical axis is the "productivity premium" for UK firms with strong inventor presence in the US between 1990 and 2000 (i.e., the differential in annual average labor productivity growth for our UK firms with above-median US inventor presence, versus those with below-median US inventor presence). The horizontal axis is average annual growth in US R&D stock. Shaded industries are those with largest US-UK TFP gap over the period (i.e., where UK firms had the "most to learn"). Industry points are weighted by number of firms in our sample. There is a positive relationship across all industries, and it is strongest in the "high-gap" sector.

We illustrate our identification strategy in Figure 1. The horizontal axis shows the average annual growth of the US R&D stock by industry between 1990 and 2000. On the vertical axis, we plot the mean "productivity premium" for UK firms that had a substantial proportion of inventors located in the US (i.e., the difference in productivity growth between UK firms with a high proportion of their inventors located in the US prior to 1990 and UK firms with zero or low US inventor presence). It is clear that the productivity premium is larger in those industries where the US had faster R&D growth. Furthermore, the shaded industries are those where the US already had a substantial technological lead over the UK in 1990 and where, presumably, UK firms had the most to learn. For these "high-gap" sectors, the upward-sloping relationship is particularly striking.

Figure 1 does not control for many other confounding influences, and the paper uses a variety of econometric methods to deal with input endogeneity, unobserved heterogeneity, and selectivity. Even after controlling for these, we find that UK firms that had more of their inventive activity located in the US *prior* to 1990 benefited disproportionately from the growth in US R&D in the 1990s. According to our estimates, US R&D during the 1990s was associated with 5-percent-higher TFP for UK manufacturing firms in 2000 (about $13 billion), with the majority of the benefits accruing to firms with an innovative presence in the US.[6]

Needless to say, our estimates present a lower bound on the full benefits of US R&D to the rest of the world. They provide, however, a salutary warning to policymakers who seek to boost

Business Expenditure on Research and Development (BERD) data) rose significantly during the early 1980s, fell back in the early 1990s, and rebounded strongly from 1994 onward. Much of the early 1980s increase was due, however, to defence-related R&D, which fell back rapidly after 1988. The growth in civil R&D intensity was strongest during the 1990s (civil R&D is likely to have greater international spillover potential than military R&D).

[6] Value added in UK manufacturing was £154 billion in 2000, about $250 billion at prevailing exchange rates.

sluggish European growth through incentivizing multinationals to repatriate US R&D back toward Europe.[7] This could be self-defeating if overseas R&D helps channel international spillovers to European countries. From the US point of view, our results suggest that while US R&D does generate large spillover benefits for the rest of the world, foreign firms must actually invest in innovative activity in the US in order to reap the full returns.

Our research has links to several strands in the literature. First, there is much work suggesting that knowledge spillovers are partly localized and that being geographically close to innovators matters.[8] We build on this work by focusing on the location of inventors *within* firms across geographic boundaries. Second, except for some aggregate studies,[9] most of the work on multinationals focuses on the benefits to the *recipient* country of inward FDI.[10] In contrast, we examine whether outward innovative FDI to specific industries in a leading-edge country has beneficial effects on home country productivity. Third, although some recent research has examined the evidence for technology sourcing through patent citations,[11] we are aware of *no* studies that consider empirical evidence for technology sourcing in terms of its effects on firm-level productivity.[12] We also show that cross-country patent citations (at the firm level) are consistent with our results, but we believe that the impact of US technology on foreign firm performance may not be fully revealed in patent citations, as some of the knowledge created is tacit rather than codified. This is captured in our TFP results, but would be overlooked if we focused only on citations.

The structure of this paper is as follows. Section I sets out the empirical model and Section II describes the data. Section III presents the empirical results, and a final section concludes. Further details of the data and models can be found in the Web Appendices (http://www.e-aer.org/data/dec06/20040910_app.pdf).

I. The Empirical Model

Our basic approach follows Zvi Griliches (1979) and many subsequent papers by including measures of the external knowledge stock available to the firm in a firm-level production function. In our main specification, we consider a conventional Cobb-Douglas production function for firms in the UK, augmented with industry-level domestic and foreign external knowledge stocks:

$$Y_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} R_{it}^{\alpha_r} DOMESTIC_{jt}^{\gamma_{i1}} FOREIGN_{jt}^{\gamma_{i2}}, \tag{1}$$

where i indexes a firm, j indexes the firm's industry, and t indexes the year. Y_{it} is real value added, A_{it} is a productivity shifter (discussed below), L_{it} is employment, K_{it} is the physical capital stock, R_{it} is the firm's own R&D stock,

[7] The European Union has set itself the target of increasing R&D expenditure located in member countries to 3 percent of GDP by 2010.

[8] For example, see Adam Jaffe et al. (1993), David Audretsch and Marion Feldman (1996), and Wolfgang Keller (2002). Paul Almeida and Bruce Kogut (1999) show that the inter-firm mobility of engineers is important for localized spillovers. Adam Jaffe and Manuel Trajtenberg (1999) find that, even after controlling for other factors, inventors residing in the same country are typically more likely to cite each other than inventors from other countries, and that these citations tend to come sooner. They also find that localization fades over time, but only slowly.

[9] For example, see Bruno van Pottelsberghe de la Potterie and Frank Lichtenberg (2001).

[10] For example, see Wolfgang Keller and Stephen Yeaple (2003) for recent US evidence, and Beata Smarzynska (2004) for evidence from Lithuania.

[11] Lee Branstetter (forthcoming) uses patent citations to measure the role of foreign direct investment by Japanese firms in the US in mediating flows of knowledge between the two countries. He finds that knowledge spillovers received by the investing Japanese firms tend to be strongest via R&D and product development facilities, which is consistent with our findings. Tomoko Iwasi and Hiroyuki Odagiri (2004) claim that Japanese research facilities foster the innovative activity of the investing parent firm using cross-sectional evidence. Jasjit Singh (2005) uses patent citations to investigate the role of multinational subsidiaries in knowledge diffusion. He finds that greater multinational subsidiary activity increases cross-border knowledge flows between the host country and the multinational home base.

[12] Lee Bransetter (2001) enters the US R&D pool in a Japanese production function and finds a positive, but insignificant, coefficient. He does not allow the effect to differ with Japanese inventor presence in the US, however (a test of technology sourcing). In addition, the author is not confident in the quality of the Japanese R&D stock data, because of the short time span (p. 72).

and $DOMESTIC_{jt}$ and $FOREIGN_{jt}$ are the R&D stocks in the firm's industry in the UK and the US, respectively.[13] Our main interest in this paper is whether the effect of the foreign external knowledge stock on productivity (captured by γ_{i2}) depends on the geographic location of the firm's innovative activity. We assume that the elasticities of value added with respect to the domestic and external knowledge stocks are a linear function of firm-specific measures of the location of innovative activity,

$$(2) \quad \gamma_{i1} = \theta_1 + \theta_2 W_i^{UK}; \quad \gamma_{i2} = \phi_1 + \phi_2 W_i^{US},$$

where W_i^{US} denotes the share of a firm's innovative activity in the US and W_i^{UK} denotes the share of a firm's innovative activity in the UK.[14] We interpret a positive estimate of ϕ_2 as evidence of knowledge spillovers associated with technology sourcing from the US. We parameterize the productivity shifter as

$$(3) \qquad \ln A_{it} = \phi_3 W_i^{US} + \theta_3 W_i^{UK} + \delta' z_{it} + \varepsilon_{it},$$

where z_{it} are controls such as demand shifters and ε_{it} is a stochastic error term whose properties we discuss in the next section. Using lowercase letters to denote natural logarithms (i.e., $x = \ln(X)$), we obtain our empirical model:

$$\begin{aligned}(4) \qquad y_{it} = {} & \alpha_l l_{it} + \alpha_k k_{it} + \alpha_r r_{it} \\ & + \theta_1 \text{domestic}_{\text{jt}} + \phi_1 \text{foreign}_{\text{jt}} \\ & + \theta_2 (W_i^{UK} * \textit{domestic}_{jt}) \\ & + \phi_2 (W_i^{US} * \textit{foreign}_{jt}) + \phi_3 W_i^{US} \\ & + \theta_3 W_i^{UK} + \delta' z_{it} + \varepsilon_{it}.\end{aligned}$$

[13] We investigated using other foreign countries as well as the US, but found no evidence of technology sourcing effects. This is not to say that the UK learns only from the US; rather the US is by far the most important partner.

[14] Again we investigated alternative functional forms, but these did not change the main qualitative results. In particular, we discuss robustness tests using the absolute volume of foreign innovative activity, rather than the relative amount of foreign innovative activity (i.e., the number of US inventors, rather than the proportion of all inventors located in the US).

A. *Econometric Issues*

There are a number of econometric issues involved in estimating firm-level production functions such as equation (4). The basic issue is how to deal with the endogeneity of the firm's input choices in the presence of unobserved heterogeneity. Our basic approach follows the "System" General Method of Moments (SYS-GMM) approach of Richard Blundell and Stephen Bond (2000). We compare these results to those from an extension to the method of Steve Olley and Ariel Pakes (1996) and to simple OLS estimates. Econometric details are contained in on-line Appendix B, but we note some features here.

The generic problem of estimating a firm production function is that the firm's input choices are likely to be correlated with the productivity shock, ε_{it} (Jacob Marshak and William H. Andrews, 1944). We assume that the residual term has the form $\varepsilon_{it} = t_t + \eta_i + u_{it}$, where year dummies ($t_t$) control for common macro effects; the unobservable firm component (η_i) is allowed to be correlated with the factor inputs (l_{it}, k_{it}, r_{it}), but assumed uncorrelated with the location of innovative activity (W_i^{US}, W_i^{UK}); and all industry-level variables and the residual productivity shock (u_{it}) may be correlated with the factor inputs.[15] Assumptions over the initial conditions yield moment conditions for the levels equations which can be combined in a system with the traditional moment conditions for the first differenced equations (generated by assumptions over the serial correlation properties of the u_{it} term). In both equations we essentially use lagged values to construct instrumental variables for current variables.

The Olley-Pakes (OP) algorithm is based on a structural model which generates a two-step method. In the first step, we obtain a consistent estimate of the labor coefficient (α_l) using a nonparametric approach to sweep out the correlation of variable inputs with the unobservable productivity state. In the second step, we

[15] In the robustness section, we discuss in detail methods of conditioning on observables to control for the components of η_i that might be correlated with W_i^{US} or W_i^{UK}.

obtain the parameters on the quasi-fixed inputs (α_k, α_r) using nonlinear least squares. We also control for selection effects using the OP approach in a nonparametric manner.

Whether we use OLS, GMM, or OP, we still have the intrinsic problem that the coefficients on our R&D spillover terms may reflect other shocks correlated with demand or supply.[16] We attempt to control for such biases by including industry fixed effects and other industry variables in the z vector (such as sector-level demand terms and industry-specific time trends). We also try using lags of the spillover terms, which should be less affected by contemporaneous shocks. The key variable of interest for us is the coefficient on the interaction term between the location weight and foreign R&D (ϕ_2, the coefficient on $W_i^{US} * foreign_{jt}$). There is no obvious reason why there would be an upward bias to this interaction term, even if there were upward bias to the linear international spillover term (ϕ_1, the coefficient on $foreign_{jt}$).

A related concern is that W_i^{UK} and W_i^{US} are choice variables for the firm, and may thus be correlated with firm- or industry-level technological shocks in a way that undermines our identification strategy. To mitigate this problem, we use *presample* information to construct W_i^{UK} and W_i^{US}. This ensures that the locational variables are not affected by shocks that also directly affect firm-level outcomes during the sample period.[17] This strategy assumes that the firm did not locate R&D in the US in anticipation of positive shocks to productivity. While we cannot rule out such behavior, the fact that the firm's patents are the result of R&D decisions taken many years prior to the period over which we estimate the production functions means that such biases are likely to be small.

A final worry is that our empirical measure of W_i^{US} may be proxying for other nonlocational aspects of firms' activities (e.g., "absorptive capacity" or technological proximity) or noninnovation-related aspects of the firm (e.g., its sales in the US). Since we have no convincing exogenous instruments for the location of firms' innovative activity, we cannot directly identify the treatment effect of location on access to R&D spillovers. Instead, we carefully test for these alternative explanations in the results section by bringing other types of data to bear upon the problem, including the technological profile of firms' patenting and the geographical location of firms' sales.

II. Data

Our main dataset is a panel of 188 manufacturing firms listed on the London Stock Exchange in 1985. These firms account for a large proportion of UK R&D activity: in 1996, near the middle of our sample period, their combined R&D expenditure was £5.1 billion, compared to total UK manufacturing business expenditure on R&D of £7.3 billion.[18] To this panel we match information on all the patents taken out by these firms at the US Patent and Trademark Office (USPTO) since 1975 (using the NBER/Case Western Patents dataset).[19] Table 1 shows that firms in our sample had 38,160 patents. Of these patents, 37 percent had the lead inventor located in the UK (column 2, Table 1), compared to only 3 percent of all USPTO patents (column 4, Table 1). This is unsurprising, since these are all firms listed on the London Stock Exchange. A further 39 percent of the patents taken out by our UK firms had the lead inventor located in the US. This illustrates the importance of the US as a location for the inventive activity of UK firms, but it may also reflect the fact that we are using USPTO patents rather than UK or European Patent Office patents.[20]

[16] See Charles Manski (1993) for a general discussion of the "reflection" problem. Note that this is more likely to be a problem for the coefficients on the domestic R&D spillover terms (θ_1, θ_2) than the foreign R&D spillover terms (ϕ_1, ϕ_2), since UK firms produce more domestically than in the US.

[17] This has the disadvantage that firms may have moved their inventive activity over time. This should, however, bias against us finding evidence of technology sourcing.

[18] These totals are not exactly comparable, since one is based on published accounts while the other is taken from the official BERD data.

[19] The patents were matched to firms using the name of the assignee. This was done manually using a register of the names of all subsidiaries of firms in our sample.

[20] A general bias toward US inventors should not be a problem for our results. It would be a problem only if the bias systematically varied with the growth in the US R&D

TABLE 1—COUNTRY OF INVENTOR

Country of inventor	(1) Number of patents matched to our UK firms	(2) % Share of patents matched to our UK firms	(3) % Share of patents matched to US firms	(4) % Share of all USPTO patents
UK	14,058	36.8	1.1	3.0
USA	14,856	38.9	92.3	55.7
Japan	2,886	7.6	1.5	18.8
Germany	1,647	4.3	1.3	7.9
France	1,117	2.9	0.9	3.0
Other	3,596	9.4	2.9	11.6
Total	38,160	100	100	100

Notes: First two columns give lead inventor location for patents matched to the 188 UK firms in our sample. Column 3 gives the lead inventor location for a sample of 570 US firms from Hall et al. (2001). Final column gives lead inventor location for all patents registered at the US Patent Office between 1975 and 1998.

For comparison, we use similar data on US firms based on the match between Compustat and the USPTO conducted by Bronwyn Hall et al. (2001, 2005). The distribution of inventors in these firms is shown in the third column of Table 1, where we see that only 1 percent of lead inventors were located in the UK, compared to 92 percent in the US. This illustrates one of the reasons why it would be hard to examine technology sourcing from US data alone.

Table 2 gives some further descriptive statistics on our UK firm sample. Since all these firms are listed on the Stock Exchange, they are larger than typical UK firms (the median employment is 1,795). Full details of the data construction are in on-line Appendix A.

The key variable of interest is inventive activity in the US, denoted W_i^{US}. Our basic measure of this is constructed as the proportion of the firm's total patents applied for between 1975 and 1989 (P_i) where the lead inventor is located in the US (P_i^{US}).[21] We construct the equivalent for the UK, denoted W_i^{UK}, which represents the share of patents where the lead inventor is located in the UK. Both W_i^{US} and W_i^{UK} equal zero if the firm applied for no patents during that period. Our firm panel of R&D and production data runs from 1990 to 2000, so the location measures are based purely on presample information. As discussed above, this ensures that the location measures are not affected by shocks that affect firm-level outcomes during the sample period.[22] This measure of the geographical location of inventive activity discards variation over time, but changes in patenting from year to year would not be a good representation of the changing location of R&D.

An alternative definition of W_i^{US} (or W_i^{UK}) is simply to use the absolute number of US inventors (P_i^{US}). Although we investigate this alternative approach empirically, normalizing P_i^{US} by the firm's total number of patents (P_i) is attractive on several grounds. First, the *number* of US inventors is highly correlated with the *total number* of patents (the correlation coefficient is 0.9 across firms in the sample) so an interaction term between P_i^{US} and US R&D could simply be picking up the effect that more innovative firms find it easier to absorb international spillovers.[23] By contrast, P_i^{US}/P_i is not significantly correlated with the total number of patents (the correlation coefficient is 0.02). Second, using the share avoids conflating our loca-

stock. In addition, almost all UK patents of significant value are registered with the USPTO.

[21] Patents have been used as indicators of the location of inventive activity in a large number of papers. For discussions of the advantages and disadvantages of patents statistics in general, see Griliches (1990). For discussions of the use of patents statistics as indicators of the location of inventive activity, see Bart Verspagen and Wilfred Schoenmakers (2004) and Zoltan J. Acs et al. (2000).

[22] We also tried a measure of W_i that used data only in the 1990s. This gave similar but slightly stronger results.

[23] In the robustness section, we investigate whether the absolute amount of inventive activity by a firm helps in "absorbing" international spillovers.

TABLE 2—DESCRIPTIVE STATISTICS

	Mean	Median	Standard deviation
Firm-level variables			
Employees	11,256	1,795	29,167
Value added (£m)	390	50.4	960
Capital stock (£m)	549	51.1	1477
R&D stock (£m)	152	1.8	627
R&D stock/value added	0.160	0.047	0.276
W_i^{US} location measure	0.351	0.213	0.382
W_i^{US} location & citation	0.317	0.194	0.351
W_i^{US} loc. & cit. within 3 yrs.	0.121	0.016	0.172
W_i^{UK} location measure	0.272	0.019	0.350
W_i^{UK} location & citation	0.064	0.000	0.132
W_i^{UK} loc. & cit. within 3 yrs.	0.014	0.000	0.046
Industry-level variables			
ln(UK R&D stock)	7.264	7.674	1.381
ln(US R&D stock)	9.798	9.572	1.241

Notes: Sample includes 188 firms, 1990–2000; all monetary amounts are in 1995 currency, deflated using OECD two-digit industry price deflator; firm-level value added is constructed as the sum of total employment costs, operating profit, depreciation, and interest payments; capital stocks and R&D stock are constructed using a perpetual inventory method.

tional measure with different propensities to patent across industries.

In order to show that our measure of inventor location is capturing what we want, we consider refining it in two ways. We focus on patents that can be seen to be drawing on: (a) US-based R&D, and (b) very recent technological developments. A key theme in the literature is that technology sourcing is not the only motivation for firms to locate innovative activity abroad. In particular, firms may conduct R&D overseas in order to adapt existing technologies to new markets. Our empirical approach to this issue is to use data on citations to focus on patents that are most likely to represent technology sourcing behavior. Consider two extreme cases for a patent owned by a UK firm but invented in the US. The first is where the patent cites only other patents owned by the same parent firm and whose inventors were located in the UK. This patent is more likely to represent activity associated with adapting an existing technology to the US market. The other extreme is where the patent cites many other patents not owned by the parent firm and whose inventors were located in the US. This patent is more likely to represent technology sourcing behavior. We want to investigate whether there is evidence for technology sourcing behavior in productivity outcomes, so we focus on the latter.

To implement this approach, our second measure of W_i^{UK} and W_i^{US} (denoted location & citation in Table 2) uses only patents that cite other patents whose lead inventors were located in the same country and were not owned within the same parent firm. This measure of W_i^{US} is thus equal to the proportion of the firm's patents where: (a) the lead inventor is located in the US, and (b) the patent cites at least one other patent whose lead inventor was located in the US and which was not owned by the same parent firm.

Our third, and most refined, measure of W_i^{UK} and W_i^{US} (denoted location & citation within 3 years in Table 2) is the same as the second measure, except it also uses information on the time lag between the citing and cited patent. Technology-sourcing behavior is likely to be associated with gaining access to pools of "tacit" knowledge. Given that knowledge created recently is more likely to have tacit characteristics, we include only citations to patents whose application date is no more than three years prior to that of the citing patent. The third measure of W_i^{US} is thus equal to the proportion of the firm's total patents where: (a) the lead inventor is located in the US, and (b) the patent cites at least one other patent applied for within the previous three years, whose lead inventor was located in the US, and which was not owned by the same parent firm. If the technology sourcing hypothesis is correct, the relationship should become stronger as we move from the least refined to the more refined measures of W_i^{US}. Descriptive statistics on our measures of W_i^{UK} and W_i^{US} are presented in Table 2.

III. Results

We start by presenting our main results, which use variation in the location of innovative activity across UK firms to identify technology sourcing from the US. We then look across UK industries, which vary in their distance to the technological frontier. We expect to see stronger technology sourcing effects for firms in UK industries where there is "most to learn" from the US. Finally, we carry out a number of robustness exercises to examine whether our interpretation of W_i as representing the location of innovative activity is robust to a range of measurement issues and alternative hypotheses.

A. *Main Results*

The main results from our R&D augmented production functions are presented in Table 3. Columns 1 and 2 present the OLS results. Column 1 does not impose constant returns to scale in labor and capital, while column 2 does.[24] Columns 3 through 5 present SYS-GMM results and column 6 presents the Olley-Pakes results. Column 3 contains the basic measure of location (i.e., the proportion of inventors based in the US), whereas the next two columns present the refinements based on citation patterns discussed above. These refined measures aim to capture technology sourcing behavior by firms more accurately. In all columns, the coefficient on the labor-capital ratio is similar to the OLS case (about 0.65, close to labor's share in value added). The estimated elasticity with respect to firm-specific R&D is positive and corresponds to a private excess rate of return to R&D of about 14 percent for our average firm, which is similar to that found in other studies.[25] Diagnostic tests are presented (bottom of the table) for first- and second-order serial correlation in the first-differenced residuals. We cannot reject the hypothesis of no serial correlation at the 5-percent level for second-order serial correlation in u_{it}. This justifies the use of levels dated $(t - 2)$ as instruments in the difference equation and differences dated $(t - 1)$ as instruments in the levels equation.[26] A Sargan-Hansen test of the overidentifying restrictions is not significant at the 5-percent level, and neither is a Sargan difference test of the extra moment conditions implied by the levels equation, indicating that our instruments are valid.

Turning to our main variables of interest, the coefficient on the key interaction term (ϕ_2) between US inventor location and the US R&D stock is positive and significant at the 5-percent level across all specifications in Table 3, except in column 3, where it is significant at the 10-percent level. This is consistent with a technology sourcing interpretation: UK firms with a stronger inventor presence in the US benefit disproportionately from US R&D spillovers. In all the GMM specifications, the linear UK R&D stock is also positive and significant, suggesting the existence of domestic spillovers, in addition to international spillovers from technology sourcing. The linear US industry R&D stock and the interaction between W_i^{UK} and UK

[24] The hypothesis of constant returns to scale is not rejected in the SYS-GMM results and is marginally rejected for OLS.

[25] For example, Griliches (1992) reports estimates of private excess rates of return ranging from 10 percent to over 50 percent. The private rate of return is calculated as $\hat{\beta} * (Y/R)$, which at the average UK firm's R&D stock intensity is $0.023 * 6.25 = 0.14$.

[26] In addition, none of the key results is sensitive to more conservative assumptions over endogeneity (i.e., if we allow for higher-order autocorrelation by dropping all the instruments back one period). In this experiment we dropped all instrumental variables dated (*t*-2) in the differenced equations and used only instruments dated (*t*-3) through (*t*-5). Similarly, we replaced instruments dated (*t*-1) with instruments dated (*t*-2) in the levels equations. Even with these more conservative timing assumptions, the key interaction term has a coefficient of 0.173 with a standard error of 0.055 in the context of a column 5 specification.

TABLE 3—R&D-AUGMENTED PRODUCTION FUNCTIONS

	(1)	(2)	(3)	(4)	(5)	(6)
Estimation method	OLS	OLS	GMM	GMM	GMM	Olley-Pakes
Dependent variable	$\ln(Y)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y)_{it}$
Location weight: W_i	—	Location	Location	Location & citation	Location & citation within 3 years	Location & citation within 3 years
$\ln(L/K)_{it}$	—	0.658	0.649	0.650	0.645	—
labour-capital		(0.046)	(0.063)	(0.064)	(0.067)	
$\ln(L)_{it}$	0.620	—	—	—	—	0.597
labour	(0.057)					(0.042)
$\ln(K)_{it}$	0.343	—	—	—	—	0.305
capital	(0.042)					(0.071)
$\ln(R\&D)_{it}$	0.029	0.012	0.023	0.024	0.022	0.014
firm R&D stock	(0.008)	(0.007)	(0.012)	(0.011)	(0.011)	(0.006)
$W_i^{US} * \ln(US\ R\&D)_{jt}$	—	0.076	0.068	0.085	0.174	0.130
% inventors in US * ln(US industry R&D stock)		(0.024)	(0.037)	(0.032)	(0.054)	(0.061)
$W_i^{UK} * \ln(UK\ R\&D)_{jt}$	—	0.035	0.028	0.093	0.401	0.081
% inventors in UK * ln(UK industry R&D stock)		(0.022)	(0.030)	(0.094)	(0.289)	(0.521)
$\ln(US\ R\&D)_{jt}$	—	0.050	0.061	0.056	0.060	0.065
US industry R&D stock		(0.118)	(0.069)	(0.067)	(0.067)	(0.091)
$\ln(UK\ R\&D)_{jt}$	—	0.273	0.263	0.257	0.243	0.147
UK industry R&D stock		(0.165)	(0.104)	(0.104)	(0.100)	(0.139)
W_i^{US}	—	−0.696	−0.622	−0.771	−1.664	−1.245
% inventors in US		(0.240)	(0.360)	(0.323)	(0.544)	(0.610)
W_i^{UK}	—	−0.296	−0.261	−0.764	−3.275	−0.958
% inventors in UK		(0.156)	(0.197)	(0.677)	(2.522)	(4.417)
Firms	188	188	188	188	188	188
Observations	1794	1794	1794	1794	1794	1496
1st-order serial correlation test	—	—	−1.22	−1.21	−1.21	—
(p-value)			*(0.224)*	*(0.225)*	*(0.224)*	
2nd-order serial correlation	—	—	−1.75	−1.77	−1.74	—
(p-value)			*(0.080)*	*(0.077)*	*(0.082)*	
Sargan difference test	—	—	29.20	29.46	28.89	—
(p-value)			*(0.302)*	*(0.291)*	*(0.316)*	
Sargan test of overidentifying restrictions *(p-value)*	—	—	86.60 *(0.190)*	86.38 *(0.195)*	86.88 *(0.185)*	—

Notes: W_i^{US} and W_i^{UK} are the (pre-1990) proportion of a firm's patents with lead inventors located in the US and UK, respectively. Standard errors in brackets are robust to heteroskedacity and autocorrelation of unknown form and are clustered by industry. The dependent variable in columns 2 through 5 is the log of value added divided by capital stock. The dependent variable in columns 1 and 6 is the log of value added. The time period is 1990–2000. Columns 1 and 2 are estimated by OLS. Columns 3 to 5 are estimated by SYS-GMM (one-step robust standard errors). In SYS-GMM (see Blundell and Bond, 2000) the time-varying firm-level variables are assumed endogenous and all other variables are 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. Column 6 is estimated by the OP method (Olley and Pakes, 1996). In OP, we use a fourth-order series expansion in the first and second stage (the second stage also includes a selection correction term). In OP, the standard errors are bootstrapped (100 replications) and allow for clustering by firm. *P*-values for diagnostic tests are in brackets and italics. All equations include a full set of industry dummies and time dummies.

industry R&D are also positive, although not statistically significant at conventional levels. The latter result suggests that locating inventors in the UK is not important for domestic spillovers, perhaps because firms find it easier to tap into domestic spillovers through other channels, for example, through membership of trade organizations.

Column 4 of Table 3 uses the refined geographical location measure W_i^{US}, which uses only patents that cited at least one other patent whose lead inventor was located in the US, as discussed in the previous section.[27] Column 5 uses the most refined measure, which includes only patents that cited at least one other patent whose lead inventor was located in the US and which was applied for within the previous three years. The two refinements bring the measure of inventor location closer to the concept of technology sourcing, although at the cost of using thinner slices of the patents data. It is reassuring that the coefficient on our key interaction ($W_i^{US} * \ln(US\ \ R\&D_{jt})$) becomes increasingly strong as we move from column 3 to column 5. This is consistent with the notion that the measures are capturing what we intend, rather than some other spurious relationship.[28]

Column 6 of Table 3 reports the OP estimates of the production function using the same refined definition of W_i^{US}, as in column 5. The coefficients on labor and capital are similar to those in the earlier columns. Most important for our purposes, the interaction between US R&D and US inventor location remains highly significant (a coefficient of 0.130 with a standard error of 0.061).[29]

Overall, there appears to be strong evidence that the productivity growth of UK firms is significantly higher if they had an inventive presence in the US prior to 1990 and operate in an industry with strong US R&D growth. This is consistent with the technology sourcing hypothesis. The estimates are economically, as well as statistically, significant. Our main results suggest that the 33-percent increase in the US R&D stock in manufacturing over 1990–2000 was associated with an average increase in the level of TFP of 5 percent for the UK firms in our sample, with the majority of the benefits accruing to firms with an innovative presence in the US. This compares with an average 6-percent-higher level of TFP associated with the increase in firms' own R&D stocks over the same period.[30]

B. *Further Investigations*

We now consider several extensions to our main results. First we investigate whether technology sourcing effects are largest in industries where the home country has "most to learn." Second, we examine an alternative definition of W_i^{US} and W_i^{UK} using the absolute number of patents located in the US and UK rather than patent shares. And third, our interpretation of W_i^{US} is that it reflects the location of innovative activity and not other firm-level characteristics. We investigate the robustness of this interpretation to three main concerns: (a) firms that locate innovative activity in the US may also locate more production activity there and/or export more to the US; our results may thus be picking up the effect of R&D in the US on exporters or producers in the US; (b) our measure of the location of innovative activity may actually be picking up unobserved heterogeneity in firms' "absorptive capacity"; (c) UK firms that locate innovative activity in the US may also be operating in technological areas that are closer to US firms, and therefore our measure of geographical proximity may actually be picking up technological proximity. Finally we discuss various other robustness tests, such as including

[27] The UK location measure W_i^{UK} is refined in the same way.

[28] It is interesting that the linear US location measures W_i^{US} are usually negative, suggesting that there is some costs to locating inventors outside the home country (although, note that this term enters positively when the interactions are not included). The median marginal effect of W_i^{US} on productivity remains positive (e.g., in column 3 the median marginal effect is 0.03, and the median marginal effect is positive in 10 out of 15 industries). It is also worth noting that the coefficient on the UK interaction term also becomes more positive as the weights become more refined, but the standard errors also increase markedly. This is probably due to the lower propensity to cite UK patents, resulting in the most refined measure of W_i^{UK} being equal to zero for most of the firms.

[29] The OP results are generated by a multistage procedure (see on-line Appendix B for details). The method is close to that implemented by Griliches and Jacques Mairesse (1998) in their firm-level R&D augmented production function on US firms. We obtained similar results using the alternative approach of Thomas Buettner (2003).

[30] These numbers are calculated as the product of the estimated elasticities from Table 3 and the percentage change in the US and own R&D stocks over the 1990–2000 period. All three location weights gave similar estimates of the contribution of US R&D to the average TFP growth of our sample of firms.

industry-specific time trends and estimating patent citation equations.

Industry Heterogeneity.—We divided industries into those where the TFP gap with the US was large versus those where the TFP gap was smaller (based on the median gap).[31] We found that the key US interaction term was much stronger in the sectors where the UK firms "had the most to learn" from the US. This is illustrated in columns 1 and 2 of Table 4. Our main coefficient of interest is more than twice as large and only statistically significant in the "high-TFP gap industries." Note also that the coefficient on the firm's own R&D stock ($R\&D_{it}$) is stronger for the sectors that have a high TFP gap with the US. This is consistent with industry-level evidence that R&D has a larger productivity impact in sectors that are further behind the technological frontier (see Rachel Griffith et al., 2004).

We also examined symmetric regressions to equation (4) for US firms to examine whether there was evidence that US firms sourced technology from the UK (results available from the authors on request). Although the relevant interaction term was positive, it was not significant at conventional levels. This is consistent with the idea that US firms benefit less from UK research because UK firms are further behind the technological frontier.[32]

Patent Share or Patent Levels?—As discussed in Section II, a potential alternative to using the *share* of lead inventors that are located in the US would be to use the *absolute number* of patents with lead inventors in the US (P_i^{US}). Our main concern about this approach is that the number of firms' patents with lead inventors in the US is highly correlated with firms' total number of patents, and so could reflect the fact that more innovative firms are better at using foreign spillovers in general ("absorptive capacity") than using technology sourcing per se. We discuss other tests of absorptive capacity below, but first we investigate this issue by using the total number of patents with a US (UK) lead inventor as the measure of W_i^{US} (W_i^{UK}) in column 3 of Table 4 instead of the share measures used in Table 3. The key interaction term ($P_i^{US} * \ln(US\ R\&D_{jt})$) is positive and significant at the 10-percent level in the equivalent "baseline" specification to column 5 of Table 3. However, when we also include our preferred interaction term in column 4 of Table 4, ($P_i^{US}/P_i) * \ln(US\ R\&D_{jt})$, it enters with a positive and significant coefficient. By contrast, the coefficient on the alternative interaction term (using the number of patents) becomes smaller and is no longer significant at even the 10-percent level. These results suggest that our share measure is more highly correlated with technology sourcing than the measure based on the total number of patents.

Location of Firm Sales.—A concern is that W_i^{US} is proxying not only for the location of innovative activity but also for the degree to which UK firms have sales in the US, either through exports or through production facilities located in the US. In order to test this possibility, we used data on the geographical distribution of firms' sales across countries to construct firm-level measures of the average proportion of sales that are in the US and the UK, denoted S_i^{US} and S_i^{UK} respectively.[33] When we entered these measures of the location of sales in the same way as W_i^{US} and W_i^{UK} in the specifications in Table 3, neither the interactions nor the linear terms entered significantly. In addition, our existing results were not affected.[34]

We then examined using a measure of the

[31] The industry split is the same as that in Figure 1.

[32] It could also be because only about 1.1 percent of US firms' lead inventors are located in the UK, as shown in Table 1, making it hard to identify technology sourcing effects.

[33] The data needed to construct this measure are available in at least one year for 88 percent of our firms. We use it as a cross-sectional measure, as the time series variation is limited and is likely to have a large noise component. The (unweighted) means of the proportion of our firms' sales that are in the US and UK are 19 percent and 48 percent, respectively (see on-line Appendix A for details).

[34] When only the location of sales interactions was included, the coefficient (standard error) on the US sales interaction term ($S_i^{US} * \ln(US\ R\&D_{jt})$) was 0.018 (0.126). When we also included our key inventor location interactions from column 5 of Table 3, the coefficient (standard error) on the key US interaction ($W_i^{US} * \ln(US\ R\&D_{jt})$) was 0.176 (0.067).

TABLE 4—R&D AUGMENTED PRODUCTION FUNCTION RESULTS—FURTHER INVESTIGATIONS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation method	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Dependent variable	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$
Sample	High TFP gap with USA	Low TFP gap with USA	All	All	All with foreign sales data	All	All	All with foreign sales data
Location weight	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years
$\ln(L/K)_{it}$ labour-capital	0.732 (0.070)	0.626 (0.119)	0.628 (0.071)	0.636 (0.069)	0.688 (0.071)	0.628 (0.066)	0.638 (0.068)	0.682 (0.072)
$\ln(R\&D)_{it}$ firm R&D stock	0.015 (0.009)	0.004 (0.013)	0.033 (0.013)	0.030 (0.013)	0.018 (0.012)	0.031 (0.013)	0.028 (0.013)	0.027 (0.013)
$W_i^{US} * \ln(US\ R\&D)_{jt}$ % inventors in US * ln(US industry R&D stock)	0.277 (0.138)	0.125 (0.093)	—	0.139 (0.062)	0.178 (0.062)	0.146 (0.051)	0.160 (0.053)	0.147 (0.058)
$W_i^{UK} * \ln(UK\ R\&D)_{jt}$ % inventors in UK * ln(UK industry R&D stock)	0.439 (0.279)	0.068 (1.326)	—	0.308 (0.251)	0.414 (0.274)	0.220 (0.300)	0.340 (0.283)	0.298 (0.290)
$P_i^{US} * \ln(US\ R\&D)_{jt}$ Number of inventors in US * ln(US industry R&D stock)	—	—	0.874 (0.457)	0.623 (0.473)	—	—	—	—
$P_i^{UK} * \ln(UK\ R\&D)_{jt}$ Number of inventors in UK * ln(UK industry R&D stock)	—	—	0.553 (2.475)	1.436 (2.532)	—	—	—	—
$S_i * \ln(US\ R\&D)_{jt}$ Share of foreign sales * ln(US industry R&D stock)	—	—	—	—	0.084 (0.062)	—	—	0.047 (0.058)
$PROX_i * \ln(US\ R\&D)_{jt}$ technology proximity to US * ln(US industry R&D stock)	—	—	—	—	—	0.113 (0.082)	—	0.064 (0.119)
$P_i * \ln(US\ R\&D)_{jt}$ Total number of patents * ln(US industry R&D stock)	—	—	—	—	—	—	0.080 (0.042)	0.095 (0.060)
$\ln(US\ R\&D)_{jt}$ US industry R&D stock	0.384 (0.170)	0.006 (0.068)	0.082 (0.066)	0.061 (0.067)	0.025 (0.076)	0.051 (0.067)	0.056 (0.067)	0.031 (0.072)
$\ln(UK\ R\&D)_{jt}$ UK industry R&D stock	0.417 (0.158)	0.008 (0.130)	0.240 (0.108)	0.220 (0.101)	0.240 (0.109)	0.231 (0.097)	0.221 (0.101)	0.227 (0.107)
W_i^{US} % inventors in US	−2.843 (1.536)	−1.203 (0.843)	—	−1.323 (0.609)	−1.778 (0.625)	−1.394 (0.505)	−1.532 (0.535)	−1.488 (0.574)
W_i^{UK} % inventors in UK	−3.487 (2.450)	−0.351 (8.760)	—	−2.434 (2.171)	−3.496 (2.352)	−1.460 (2.542)	−2.811 (2.440)	−2.184 (2.345)
P_i^{US} total number of US inventors	—	—	−9.219 (4.895)	−6.639 (5.044)	—	—	—	—
P_i^{UK} total number of UK inventors	—	—	−11.239 (21.745)	−17.295 (22.004)	—	—	—	—

TABLE 4—*Continued.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Estimation method	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
Dependent variable	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$	$\ln(Y/K)_{it}$
Sample	High TFP gap with USA	Low TFP gap with USA	All	All	All with foreign sales data	All	All	All with foreign sales data
Location weight	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years	Location & citation within 3 years
S_i % of sales that are foreign	—	—	—	—	−0.627 (0.568)	—	—	−0.191 (0.543)
$PROX_i$ technology proximity to US *	—	—	—	—	—	−1.514 (0.773)	—	−1.029 (1.108)
P_i Total number of patents	—	—	—	—	—	—	−0.959 (0.477)	−1.085 (0.668)
Firms	99	89	188	188	166	188	188	166
Observations	938	856	1794	1794	1599	1794	1794	1599
1st order serial correlation test *(p-value)*	−1.11 *(0.267)*	−2.46 *(0.014)*	−1.21 *(0.224)*	−1.21 *(0.224)*	−1.12 *(0.262)*	−1.22 *(0.224)*	−1.21 *(0.224)*	−1.12 *(0.261)*
2nd order serial correlation *(p-value)*	−0.14 *(0.888)*	−1.92 *(0.055)*	−1.94 *(0.052)*	−1.90 *(0.057)*	−1.87 *(0.061)*	−1.93 *(0.053)*	−1.87 *(0.062)*	−2.12 *(0.034)*
Sargan difference test *(p-value)*	14.98 *(0.958)*	25.52 *(0.490)*	30.06 *(0.265)*	28.86 *(0.317)*	31.25 *(0.219)*	30.36 *(0.253)*	27.67 *(0.375)*	33.53 *(0.147)*
Sargan test of overidentifying restrictions *(p-value)*	77.87 *(0.419)*	69.38 *(0.691)*	87.63 *(0.170)*	87.22 *(0.178)*	91.46 *(0.109)*	88.76 *(0.150)*	85.58 *(0.212)*	94.19 *(0.077)*

Notes: "High TFP gap" indicates those industries where the TFP gap with the US was above the median (see Figure 1). W_i^{US} and W_i^{UK} are the (pre-1990) proportion of a firm's inventors located in the US and UK, respectively. P_i^{US} and P_i^{UK} are the (pre-1990) number of inventors located in the US and UK, respectively. S_i is the proportion of firm sales that are foreign, $PROX_i$ is the technological proximity of firm i to the US industry j. Standard errors in brackets under coefficients are robust to heteroskedacity and autocorrelation of unknown form. The time period is 1990–2000. All columns are estimated by SYS-GMM (one-step robust standard errors). The time-varying firm-level variables are assumed endogenous and all other variables are assumed 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. *P*-values of diagnostic tests are in brackets and italics. All equations include a full set of industry dummies and time dummies.

average share of firms' sales that were not in the UK, denoted S_i. This includes sales in the US, other European countries, and the rest of the world, and as such can be seen as an overall measure of the internationalization of a firm's sales. When we interacted this measure with US R&D in the same way as described above, the interaction term was positive and significant.[35] The fact that the interaction of US R&D with this general internationalization measure entered significantly, while the interaction with the firms' average proportion of sales in the US did not, suggests that the relevant characteristic may be some kind of unobserved heterogeneity relating to selling abroad, rather than selling in the US particularly. However, in column 5 of Table 4 we add this interaction to the final specification in column 5 of Table 3. The interaction with the proportion of sales outside the UK ($S_i * \ln(US\ R\&D_{jt})$) becomes insignificant, and our previous results are again essentially unchanged. This provides fairly strong evidence

[35] The coefficient on the interaction ($S_i * \ln(US\ R\&D_{jt})$) was 0.122, with a standard error of 0.059.

that our key inventor location measure W_i^{US} is capturing something more than just the geographical location of firms' sales.

Knowledge Spillovers or Technological Proximity?—Another concern with our interpretation is that the UK firms that have more inventors in the US may also have closer "technological proximity" to the US. Consequently, our interaction may merely be picking up the fact that US R&D is more likely to benefit these firms, and has nothing to do with the fact that these UK firms have inventors located in the US. To investigate this possibility we construct a measure of technological proximity between our UK firms and US industries following the Jaffe (1986) method. We used data from the NBER USPTO-Compustat match (described in Hall et al., 2001) to calculate an industry-specific technological profile for the US using the average share of patents in each of the 623 technology classes in the USPTO. We then calculated the uncentered correlation coefficient between each of our UK firms and their corresponding US industry (see on-line Appendix A for more details). In column 6 of Table 4 we include this proximity measure in the baseline specification from column 5 of Table 3, both interacted with US R&D and on its own. Although the coefficient on this proximity measure interaction is positive, it is not significantly different from zero. Furthermore the coefficient on our inventor location interaction remains positive and significant at the 5-percent level.[36]

Absorptive Capacity.—Another interpretational difficulty arises if the inventor location term simply reflects the firm's total innovative efforts. For example, if UK firms with inventors located in the US are more innovative, and if innovative firms absorb international knowledge more easily, this could account for the positive interaction. As discussed above, using the *share* of patents as a measure of location goes some way toward dealing with this.[37] However, to test the absorptive capacity hypothesis, we included further interactions of the spillover measures with indicators of the firm's overall inventiveness. In column 7 of Table 4, for example, we interact the firm's total number of patents in the 1975–1989 period with the US R&D term to confirm that the results on the location interactions are not driven by more innovative firms having higher "absorptive capacity" than less innovative firms. Although the interaction is positive and significant at the 10-percent level, the inventor location interaction remains positive and significant at the 5-percent level. We also experimented with using the firm's average level of R&D as an alternative measure of innovation, and the results were similar.[38]

The concern over absorptive capacity is similar to the concern that W_i^{US} reflects some other form of unobserved heterogeneity.[39] To address this, we calculated two further measures of firm-level heterogeneity using presample information. We used the presample mean wage as a measure of worker quality and presample TFP as a measure of firm quality. Both terms were insignificant when interacted with US R&D, and our main results were not affected.[40]

Other Robustness Tests of the Production Function Results.—In the final column of Table 4, we include the extra variables we used above in our robustness tests, i.e., the controls for the location of firm sales, technological proximity, and absorptive capacity. Despite this very stringent test, the coefficient on the key interaction term, $W_i^{US} * \ln(US\ R\&D_{jt})$, remains positive and

[36] Using the whole 1975–1999 period instead of just the presample information to construct this alternative proximity weight, and including it in this regression, gave similar qualitative results as did using a proximity based on the whole of the US instead of the industry-specific profile.

[37] For example, the cross-firm correlation between the most refined US location weight and average R&D intensity is only 0.08.

[38] The coefficient on the interaction of the firm's own R&D and US industry R&D was 0.004, with a standard error of 0.003.

[39] It could also be that US R&D is intrinsically more productive, so the interaction is merely picking up "R&D quality" (e.g., if UK firms in the US hired the best scientists). To test this, we interacted the firm's own R&D with W_i^{US}. The coefficient was insignificant, whereas we would expect it to be significantly positive if US R&D was of higher quality.

[40] The *t*-statistics were 0.03 and 0.01, respectively.

significant at the 5-percent level. We also conducted a large number of other robustness checks. First, we included industry-level value added (at both two- and three-digit levels) in the US and in the UK to check that the results are not driven by industry-level shocks correlated with R&D. None of the value-added terms was significant. We also included interactions of industry-level value added with W_i^{US} and W_i^{UK}. None of these interactions was significant, and the interaction of US R&D with W_i^{US} was unaffected. Second, we included industry-specific trends to account for different rates of exogenous technological progress across industries. Again, none of the key results was affected.[41] Third, we lagged all the industry-level R&D terms by one period, so that they could be considered predetermined. Again, the main results were not affected.[42] We also considered whether the key results were driven by firms in particular industries. For example, if we drop the chemicals/pharmaceuticals industry, which is the most R&D-intensive UK industry in our sample, our results still hold, with a coefficient (standard error) on the key interaction term of 0.213 (0.069).

As a final robustness test, we follow recent studies by using citations as a direct measure of knowledge spillovers (full results are contained in Griffith et al., 2004).[43] Consistent with our results above, we find that patents taken out by UK firms with lead inventors located in the US are more likely to cite other US inventors than patents taken out by UK firms without a US lead inventor.[44] In addition, if we look at those UK firms that have a high proportion of patents with lead inventors in the US (high W_i^{US}), but consider their patents with lead inventors located in the UK, we find that these UK-based inventors are *not* more likely to cite US inventors. In other words, the high citation rates of high W_i^{US} firms to other US inventors seem to be precisely because these UK firms have many US-based inventors. These results support our findings: UK firms with inventors located in the US are more able to benefit from localized US spillovers precisely because of the presence of those inventors in the US, and not because of some other firm-level characteristic that is correlated with having inventors located in the US.

IV. Summary and Conclusions

The results presented in this paper provide strong evidence for the existence of knowledge spillovers associated with technology sourcing. The idea that foreign firms might invest in R&D activity in a technologically advanced country such as the US in order to gain access to spillovers of new "tacit" knowledge has been suggested in the business literature, but we know of no studies that have attempted to find evidence for this in observed productivity outcomes.

Our main results suggest that the increase in the US R&D stock in manufacturing between 1990 and 2000 was associated with, on average, a 5-percent-higher level of TFP for the UK firms in our sample, with the majority of the benefits accruing to firms with an innovative presence in the US. This compares with an average 6-percent-higher level of TFP associated with the increase in their own R&D stocks over the same period.

Increases in US R&D in the 1990s seem to have had major benefits for the UK economy, and, by implication, for many other countries in the world. We should stress that, because we do not have a convincing instrument for the location of inventive activity, and thus rely on presample information, we can interpret these results only as associations, and not as causal relations. Nonetheless, we believe that they are suggestive, and an interesting extension of our methods would be to replicate the findings for other countries. A larger stock of US R&D should also increase the incentives for multinationals to locate R&D in the US, which is indeed what has occurred. Future research needs to show to what extent this movement in R&D

[41] When we included industry trends, the linear US R&D term became significantly positive, suggesting some positive spillovers to firms with no US inventors. However, this result was not robust to different specifications and time periods.

[42] In an equivalent specification to that of column 5 of Table 3, the coefficient on the key interaction variable, R&D $*W_i^{US}$, was equal to 0.177 with a standard error of 0.540.

[43] See Jaffe et al. (1993), Branstetter (forthcoming), or Singh (2003).

[44] In carrying out this analysis, we exclude self citations (citations by a firm to one of its own patents).

is driven by technology sourcing rather than other potential causes.

Our result has interesting implications for policy. Governments are generally keen to promote higher levels of domestic R&D activity, and the member states of the European Union have agreed on a target to raise the level of R&D spending within the European Union to 3 percent of GDP. Our results suggest that policies that seek to achieve this target by inducing European multinationals to relocate their existing R&D efforts away from the US and toward Europe could be counterproductive, as they may reduce the ability of European firms to benefit from US-based R&D spillovers.

From an American perspective, our results suggest that while US R&D does generate large spillover benefits for the rest of the world, foreign firms must actually invest in innovative activity in the US in order to reap the full benefits. When it comes to international technology spillovers, it seems there is no such thing as a completely free lunch.

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