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How Special is the Special Relationship? Using the Impact of R&D Spillovers on UK Firms As a Test of Technology Sourcing

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Abstract
How much does US-based R&D benefit other countries and through what mechanisms? We test the "technology sourcing" hypothesis that foreign research labs located on US soil tap into US R&D spillovers and improve home country productivity. Using panels of UK and US firms matched to patent data we show that UK firms who had established a high proportion of US-based inventors by 1990 benefited disproportionately from the growth of the US R&D stock over the next 10 years. We estimate that UK firms' Total Factor Productivity would have been at least 5% lower in 2000 (about $14bn) in the absence of the US R&D growth in the 1990s. We also find that technology sourcing is more important for countries and industries who have "most to learn". Within the UK, the benefits of technology sourcing were larger in industries whose TFP gap with the US was greater. Between countries, the growth of the UK R&D stock did not appear to have a major benefit for US firms who located R&D labs in the UK. The "special relationship" between the UK and the US appears distinctly asymmetric.

JEL Classifications. O32, O33, F23
Keywords: international spillovers; technology sourcing; productivity; patents, R&D

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1. Introduction

There is a consensus among economists and policy makers that an important part of global economic growth arises from the transfer of ideas from the leading edge countries to those behind the frontier. However, the mechanisms underlying this technology transfer are poorly understood, and micro-econometric 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, 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.[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 by exploiting firm level panel data from the UK and the US. UK firms offer a particularly good testing ground for this hypothesis because Britain is both less technologically advanced than the US[3] and has historically close linkages to US based inventors.[4] We examine whether the US R&D stock (conditional on UK

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

[2] See for example von Zedtwitz and Gassman (2002) or Serapio and Dalton (1999) and the references therein.

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

[4] Of all foreign countries, British expenditure on R&D in the US was second in the world only to Switzerland in 1993. In 1997, of the largest 7 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 were produced by inventors located in the US.

R&D) had a stronger impact on the TFP of UK firms who 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.

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 "productivity premium" for UK firms who 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 around here]

The graph 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 which 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, TFP in British manufacturing in 2000 would have been 5% lower (representing around \$14bn)[5] in the absence of the growth in US R&D stock that

[5]Value added in UK manufacturing was £154bn in 2000, about \$275bn at current exchange rates

occurred over the 1990s. Needless to say, this is a lower bound on the full benefits of US R&D to the rest of the world. It is also a salutary warning to policy makers who seek to boost sluggish European growth through incentivising multinationals to repatriate US R&D back towards Europe.[6] This could be self defeating if overseas R&D helps channel international spillovers to European countries.

Theory suggests that technology sourcing effects should be largest in industries where the home country has "most to learn". We look across UK industries and find the benefits of technology sourcing to be largest in those industries that lie furthest behind the US in technological terms (see Figure 1). As well as this within-country evidence we also look across countries. We contrast our UK production functions with identical specifications based on US firm level panel data. Although it is possible that US firms source technology from the UK, it is likely to be much less important, as firms in the UK are generally not at the technological frontier. This is indeed what we find: spillovers associated with technology sourcing from the UK to the US are small in economic and statistical terms. The "special relationship" between the UK and the US is asymmetric: the UK benefits more when it comes to knowledge flows.

Our research has links to several strands in the literature. First, there is much work suggesting that knowledge spillovers are partly localised and that being geographically close to innovators matters.[7] We build on this work by focusing on the location of inventors *within* firms across geographic boundaries. Second, except for

[6] The European Union has set itself the target of increasing R&D expenditure located in member countries to 3% of GDP by 2010 (this is part of the "Lisbon Agenda").

[7] For example, Adam Jaffe et al (1993, 2000), Wolfgang Keller (2002), David Audretsch and Marion Feldman (1996). Adam Jaffe and Manuel Trajtenberg (1998) 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 localisation fades over time, but only slowly.

some aggregate studies,[8] most of the work on multinationals focuses on the benefits to the *recipient* country of inward FDI.[9] In contrast, we examine whether outward innovative FDI to specific industries in a leading edge country has beneficial affects on home country productivity. Thirdly, although there is some recent research that has examined the evidence for technology sourcing through patent citations,[10] we are aware of *no* studies that consider empirical evidence for technology sourcing in terms of its effects on firm-level productivity.[11] 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 missed if we focused only on citations.

The structure of this paper is as follows. Section 2 sets out the empirical model and Section 3 describes the data. Section 4 presents the empirical results, and a final section concludes. The details of the data and models are in the Appendices.

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

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

[10] Lee Branstetter (2003) 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 (2002) claim that Japanese research facilities foster the innovative activity of the investing parent firm, but they only have cross sectional evidence. Singh (2003) 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.

[11] 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).

2. 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[12]

$$Y_{it} = A_{it} L_{it}^{\alpha_l} K_{it}^{\alpha_k} R_{it}^{\beta} DOMESTIC_{jt}^{\gamma_{i1}} FOREIGN_{jt}^{\gamma_{i2}} \tag{2.1}$$

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 a measure of the firm's capital stock, R_{it} is a measure of the firm's own R&D stock, 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 geographical 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,[14]

$$\gamma_{i1} = \theta_1 + \theta_2 W_i^{UK}; \quad \gamma_{i2} = \phi_1 + \phi_2 W_i^{US}; \tag{2.2}$$

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. We interpret a posi-

[12] We considered more flexible functional forms such as a translog, but we could not reject the Cobb-Douglas specification, and none of the key results were affected.

[13] We investigated using other foreign countries as well as the US. The results are discussed in the robustness section below.

[14] Again we investigated more flexible functional forms, but these did not change the main qualitative results.

tive estimate of ϕ_2 as evidence of knowledge spillovers associated with technology sourcing from the US. Using lower case letters to denote natural logarithms (i.e. $x = \ln(X)$) we obtain:

$$\begin{aligned} y_{it} &= \alpha_l l_{it} + \alpha_k k_{it} + \beta r_{it} + \theta_1 domestic_{jt} + \phi_1 foreign_{jt} + \theta_2 (W_i^{UK} * domestic_{jt}) \\ &\quad + \phi_2 (W_i^{US} * foreign_{jt}) + \phi_3 W_i^{US} + \theta_3 W_i^{UK} + a_{it}. \end{aligned} \tag{2.3}$$

Our baseline specification is for UK firms, but we estimate a symmetric equation for US firms to see if technology sourcing from the UK matters for the US. As stated above, we expect it to be much less important, as the UK is generally not at the technological frontier in the vast majority of industries.

2.1. Econometric issues

There are a number of econometric issues involved in estimating firm level production functions such as equation (2.3). 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 Olley-Pakes (1996) method which allows for endogenous R&D and to simple OLS. Econometric details are contained in 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, a_{it}. Under SYS-GMM we assume that the residual term can be broken down into $a_{it} = t_t + \eta_i + u_{it}$, where year dummies ($t_t$) control for common macro effects, the firm fixed effect (η_i) controls for unobserved heterogeneity and the residual productivity shock (u_{it})

may be correlated with the regressors. 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 labour coefficient (α_l) using a non-parametric approach to sweep out the correlation of variable inputs with the error term. In the second step we obtain the capital parameter (α_k) using non-linear least squares. The routine avoids using instrumental variables, but does not extend so straightforwardly to endogenous R&D decisions. We therefore consider an extension to Olley-Pakes which allows for endogenous R&D, following Thomas Buettner (2004). This leaves stage one of the algorithm intact, but alters the way we draw inferences on the capital coefficient at stage 2.

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.[15] We attempt to control for such biases by including firm (or industry) fixed effects and other industry variables (such as sector-level demand terms and industry specific trends). We also try using lags of the spillover terms, which should be less affected by contemporaneous shocks. Of course, 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

[15] See Charles Manski (1991) for a general discussion of what is known as 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 since UK firms mainly produce domestically.

is no obvious reason why there would be an upwards bias to this interaction term, even if there was upwards 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. Since we have no convincing exogenous instruments for the location of firms' innovative activity we use *pre-sample* 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.[16] 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 behaviour, 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 non-locational aspects of firm's activities (e.g. "absorptive capacity" or unobserved firm quality) or non-innovation related aspects of the firm (e.g. its US production activities). We carefully test for these alternative explanations in the results section by bringing other types of data to bear upon the problem, including citations information and the location of production.

3. Data

Our main dataset is a panel of 188 manufacturing companies that were listed on the London Stock Exchange in 1985. These firms account for a large proportion of

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

UK R&D activity: in 1996, near the middle of our sample period, their combined R&D expenditure was £5.1bn, compared to total UK manufacturing business expenditure on R&D of £7.3bn.[17] To this panel we match information on all the patents taken out by these firms at the USPTO since 1975 (using the NBER/Case Western Patents dataset).[18] Table 1 shows that firms in our sample had 38,160 patents. Of these patents 37% had their inventors located in the UK, compared to only 3% in the USPTO population as a whole. This is unsurprising., since these are all firms listed on the London Stock Exchange. A further 39% of the patents taken out by our UK firms had inventors located in the US. This illustrates the importance of the US as a location for the inventive activity of UK firms, but it also reflects the fact that we are using USPTO patents rather than UK or European Patent Office patents.[19]

We compare our main results on UK firms with symmetric results for US firms. Our US firm data is based on the match between Compustat and the USPTO conducted by Bronwyn Hall et al (2004). The distribution of inventors in these firms is shown in the third column of Table 1, where we see that only 1% of inventors were located in the UK compared to 92% in the US itself. 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 perform R&D and are listed on the Stock Exchange they are larger

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

[18] 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.

[19] A general bias towards US inventors should not be problem for our results. It would only be a problem if the bias systematically varied with the growth in the US R&D stock. In addition, almost all UK patents of significant value are registered with the USPTO.

than typical UK firms (the median employment is 1,750). Compared to the sample of US firms, however, the UK firms are smaller (median US firm employment is 3,528). UK firms are also less R&D intensive that their US counterparts, which mirrors the aggregate statistics. Full details of the data construction are in 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 where the lead inventor is located in the USA.[20] 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. They are both equal to zero if the firm applied for no patents during that period. Our firm panel on R&D and production data runs from 1990 to 2000, so the location measures are based purely on pre-sample information. As discussed above, this ensures that the location measures are not affected by shocks that affect firm-level outcomes during the sample period. This measure of the geographical location of inventive activity discards variation over time - it represents an average of the location of the firm's innovative activity over the period 1975-1989. Variation in patenting from year to year would not be a good representation of the changing location of R&D.[21] Furthermore, normalising by the firm's total number of patents avoids conflating our locational measure with different propensities to patent across industries[22].

In order to show that our measure of inventor location is capturing what we

[20] 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 Zvi 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 Acs et al (2000).

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

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

want, we consider refining it in two ways. We focus on patents that can be seen to be drawing on US-based R&D, and on patents that can be seen to be drawing on 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 do R&D abroad 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 behaviour. Consider two extreme cases for a patent that is owned by a UK firm but that was invented in the US. The first is where the patent only cites 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 that are not owned by the parent firm and whose inventors were located in the US. This patent is more likely to represent technology sourcing behaviour. We want to investigate whether there is evidence for technology sourcing behaviour in productivity outcomes, so we want to focus on the latter, and not use the first type of patent when constructing our location measures.

To implement this approach, our second measure of W_i^{UK} and W_i^{US} looks only at patents that cite other patents whose 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: (1) the inventor is located in the USA and (2) the patent cites at least one other patent whose inventor was both 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} is the same as the second measure, except that it also uses information on the time-lag between the citing and cited patent. Technology sourcing behaviour is likely to be associated with gaining access to pools of "tacit" knowledge. Given that knowledge that was 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: (1) the inventor is located in the USA and (2) the patent cites at least one other patent that was applied for within the previous three years (and whose inventor was both located in the US and did not work for the same parent firm). If the technology sourcing hypothesis is correct the relationship should be stronger as we move from the least refined to the most refined measures of W_i^{US}.

4. Results

We start by presenting our main results, which use variation across UK firms to identify technology sourcing from the US. We then investigate two further implications: we compare our main results for UK firms to those for US firms, where we expect to see a smaller effect, and we look across UK industries, which vary in their distance to the technological frontier. We expect to see a stronger effects for the 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.

4.1. Production Function: 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 labour and capital, while column (2) does.[23] Columns (3) through (5) present System-GMM results and column (6) presents the Olley-Pakes results. Column (3) contains the basic measure of location (e.g. the proportion of inventors based in the US) whereas the next two columns present the closer refinements to technology sourcing based on citation patterns (as discussed above). In all columns the coefficient on the labour-capital ratio is similar to the OLS case (about 0.65, close to labour'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 16% for our average firm, which is similar to that found in other studies.[24] Diagnostic tests are presented (bottom of the table) for first and second order serial correlation in the first-differenced residuals. Neither test ever rejects the hypothesis of no serial correlation at the 5% level. This justifies the use of twice lagged instruments in the difference equation and once lagged instruments in the levels equation.[25] A Sargan test of the overidentifying restrictions is not significant at the 5% level, and neither is a Sargan difference test of the extra moment conditions implied by the levels equation.

Turning to our main variables of interest, the key interaction term (ϕ_2) between US inventor location and the US R&D stock is positive and significant at conventional levels across all specifications in Table 3. This is consistent with a technology sourcing interpretation: UK firms with a stronger inventor presence in

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

[24] For example, Zvi Griliches (1992) reports estimates of private excess rates of return ranging from 10% to over 50%. The private rate of return is calculated as $\widehat{\beta} * (\frac{Y}{R})$ which at the average UK firm's R&D stock intensity is 0.025*6.25 = 0.16

[25] In addition, none of the key results are sensitive to dropping twice-lagged differences and replacing the once-lagged levels with twice lagged levels from the instrument set. For example, in the context of column (5) the key interaction has a coefficient of 0.173 with a standard error of 0.055.

the US benefit disproportionately from US R&D spillovers. The linear UK R&D stock is also positive and significant across all columns, 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 industry R&D are also positive in all the GMM specifications, although not statistically significant at conventional levels. The latter result suggests that locating inventors in the UK is not important for domestic spillovers.

Column (4) of Table 3 uses the refined geographical location measure W_i^{US} that uses only patents that cited at least one other patent whose inventor was located in the US, as discussed in the previous section.[26] Column (5) uses the most refined measure, which includes only patents that cited at least one other patent whose 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 theoretical ideal 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 (5). This is consistent with the notion that the measures are capturing what we intend, rather than some other spurious relationship.[27]

Column (6) reports the Olley-Pakes estimates of the production function. The coefficient on labour is slightly lower relative to OLS and the coefficient on capital

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

[27] 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 low propensity to cite UK patents, resulting in the most refined measure of W_i^{UK} being equal to zero for most of the firms.

is higher. The OLS bias is what one would expect from endogeneity of inputs and selectivity.[28] The qualitative findings are robust, however, and the interaction between US R&D and US inventor location remains highly significant.[29]

Overall, there appears to be strong evidence that the productivity growth of UK firms is significantly higher if they have an inventive presence in the US 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% 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% for the UK firms in our sample. This compares with an average 6% higher level of TFP associated with the increase in their own R&D stocks over the same period.[30] For an individual UK firm, shifting 10 percentage points of its innovative activity (as measured by patent applications) from the UK to the US while keeping its overall level of R&D stock the same (e.g. changing W_i^{US} from 0.20 to 0.30 and W_i^{UK} from 0.80 to 0.70 while keeping R_{it} the same), is associated with an increase in its TFP level of about 3%.

[28]Endogeneity of input choice generally leads to an upward bias on the labour coefficient and a downward bias on the capital coefficient as there is generally a higher contemporaneous correlation between labour and productivity than between capital and productivity (Marschak and Andrews, 1944; James Levinsohn and Amil Petrin, 2003).

[29]The OP results are generated by a multi-stage procedure (see Appendix B for details). We have included the own R&D stock as a control variable at stage 2 (like Zvi Griliches and Jacques Mairesse, 1998) although, strictly speaking, this is unnecessary in the Thomas Buettner (2003) approach. If we drop the own R&D stock the key interaction (between inventor location in the US and US R&D) is 0.115 with a standard error of 0.045 - very similar to that reported in Table 3. A further implication of this approach is that the cummulative distribution of $\Delta\omega$ should stochastically dominate (in the first order sense) for high R&D intensity firms compared to low R&D intensity firms. This implication is also accepted in our data.

[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 TFP growth of our sample of firms.

4.2. Production Function: Further Investigations

We now consider two additional implications of the hypothesis that these results indicate technology sourcing. First, technology sourcing effects should be largest in industries where the home country has "most to learn". We start by comparing our results on UK firms with a symmetric specification estimated on a panel of US firms. We expect these results to show less evidence of technology sourcing, as the US is in general more technologically advanced than the UK. Second, we return to the UK and look at how the impact of technology sourcing varies across industries. We expect the benefits of technology sourcing to be largest in those UK industries that lie furthest behind the US in technological terms.

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: (i) firms that locate innovative activity in the US may also locate production activity there, and our results may thus be picking up the effect of R&D in the US on production activity in the US; (ii) our measure of the location of innovative activity may actually be picking up unobserved heterogeneity in firms' "absorptive capacity"; (iii) UK firms that locate innovative activity in the US may also be located closer to US firms in technology space, and therefore our measure of geographical proximity may actually be picking up technological proximity

We then discuss various other robustness tests such as including industry specific time trends. Finally, in section 4.3, we carry out one further test, which is to take an entirely different approach to answering the same question. We look at patent citation equations and show that these back up our technology sourcing interpretation.

4.2.1. Results for US firms

All the results presented so far are for UK firms. This is a natural place to look for evidence of technology sourcing: given that the US is usually at the technology frontier and UK firms are generally below the technology frontier, we might expect that technology sourcing is a particularly important for UK firms investing in the US.

It is interesting to investigate whether there is symmetry to this relationship, or whether, as expected, the results are weaker for US firms investing in the UK. In column (1) of table 4 we show estimates of the symmetric specification to column (3) of Table 3. We now look at US firms rather than UK firms (see Appendix A for details of the data). The coefficients on labour and capital are similar to the GMM estimates for the UK firms. The domestic US R&D term is positive and significant, suggesting domestic spillovers, but the interaction with the location weight is insignificantly different from zero. Both these results mirror those for the UK firms. The interaction between the share of US firms' inventors located in the UK and UK industry R&D is insignificantly different from zero, although it is positive.[31] Even if the interaction were statistically significant, however, the economic magnitude of the impact is small. A US firm would have to have at least half of its inventors in the UK before UK R&D achieved any positive productivity impact (only 0.5% of the US sample are in this position). As with the UK firms, the Olley-Pakes results are similar to GMM - the key interaction term between UK inventor presence and UK R&D has a coefficient of 0.158 with a standard error of

[31] In the case of the US firms, using the increasingly refined location weights leads to increasingly imprecise and insignificant coefficients on the key interaction term. This is in contrast to the equivalent results for the UK firms presented in Table 3, where the coefficient on the key interaction becomes larger and more significant as the weights become more refined.

0.175.[32]

4.2.2. Industry Heterogeneity

Returning to the sample of UK firms, we can also look at whether the technology sourcing effect is larger for industries furthest behind the technological frontier. 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).[33] We found that the 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 (2) and (3) of Table 4. Our main coefficient of interest is more than twice as large and only statistically significant in the "high TFP gap industries". This between-industry, within-country, evidence is consistent with the between-country evidence from the comparison of results for UK and US firms in the previous section. Note also that the own R&D coefficient is much stronger for the sectors with a higher TFP Gap. This is consistent with industry-level evidence that R&D has a larger productivity impact in sectors with a larger TFP gap than in those where the gap is lower (see Rachel Griffith, Stephen Redding and John Van Reenen, 2004).

4.2.3. Location of Productive Activity

So far we have assumed that the production activity of UK firms is located entirely in the UK. However, 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, British firms with innovative activity in the US may also have productive activity located there. If this is the case, then we may be picking up not only international spillovers but also domestic

[32] The coefficient on labour is 0.567 and the coefficient on capital is 0.214.
[33] See Table A5 in the Appendix for the industry split.

spillovers within the US. We attempt to control for this by estimating our model on firms with no (or very low) US production activities (72% of our firms are in this category) based on their reported number of domestic and overseas employees.[34] In column (4) of table 4 we present results estimated on firms whose productive activity is located almost entirely within the UK. The results are very similar - the key interaction of inventor location with US R&D stock has a coefficient of 0.221 and standard error of 0.063, actually slightly stronger than in column (5) of Table 3. This suggests that our UK results are not primarily driven by the location of firms' production activities.

4.2.4. Absorptive Capacity

One 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.[35] To test this we included further interactions of the spillover measures with indicators of the firms overall inventiveness. Although these were generally positive they were less informative than the location interactions. For example, we interacted the firm's own R&D stock with the U.S. industry R&D terms. This is to check that the results on the location interactions are not driven by high R&D firms having higher "absorptive capacity" than low R&D firms. We performed a similar exercise with patenting firms. Although these interactions were positive they were not signifi-

[34] 117 out of 188 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 117 firms, 53 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 135 firms, which we expect to have little or no foreign production activity.

[35] Although the cross-firm correlation between the most refined US location weight and average R&D intensity is only 0.08.

cant at conventional levels.[36] Furthermore, the interaction of US R&D with W_i^{US} also remained positive and significant, suggesting that the results are not driven by absorptive capacity.

The concern over absorptive capacity is similar to the concern that W_i^{US} reflects some other form of unobserved heterogeneity.[37] To address this we calculated two further measures of firm-level heterogeneity using pre-sample information. We used the pre-sample mean wage as a measure of worker quality and pre-sample TFP as a measure of firm quality. Both terms were insignificant when interacted with US R&D.[38] We conduct a further test of the role of unobserved firm heterogeneity using a patents citation equation in sub-section 4.3.

4.2.5. Knowledge Spillovers or Technological Proximity?

Another concern with our interpretation is that the UK firms who 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 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 the Compustat firms described in sub-section 4.2.1 to calculate an industry specific technological profile using the average share of patents in each of the 623 technology classes in the USPTO. We then cal-

[36] The t-statistic on the interaction of the firms' ln(R&D) with ln(US industry R&D) was 1.5 (coefficient 0.002). The interaction of ln(US R&D) with a dummy if the firm had patented had a t-statistic of 1.2 (coefficient 0.033).

[37] 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 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.

[38] The t-statistics were 0.03 and 0.01 respectively.

culated the uncentered correlation coefficient between each of our UK firms and their corresponding US industry (see the Appendix for more details). This proximity measure was interacted with US R&D and included in the regression (along with the linear proximity term). Although this proximity measure interaction was consistently positive, it was statistically dominated by our inventor location interaction. For example, including the technological proximity interaction in our preferred column (5) of Table 3 gave a coefficient(standard error) of 0.108 (0.074) compared to an inventor location interaction of 0.156 (0.048).[39]

4.2.6. Other Robustness Tests of the Production Function

We also conducted a large number of other robustness checks. First, we included industry level value added (at both 2 and 3 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 is significant in the UK equations.[40] We also included interactions of industry level value added with W_i^{US} and W_i^{UK}. None of these interactions were significant, and the interaction of US R&D with W_i^{US} was unaffected. Secondly, we included industry specific trends to account for different rates of exogenous technological progress across industries. Again none of the key results were affected.[41] Thirdly, we lagged all the industry level R&D terms by one period, so that they could be considered pre-determined. Again the main results

[39] Using the whole 1975-1999 period to construct this alternative proximity weight and including it in this regression gave a similar result (0.111 (0.089)) as did using a proximity based on the whole of the US instead of the industry-specific profile.

[40] US value added was significant in the US firms production function and we keep it in the Table 4 column (1) results to control for domestic industry-level shocks.

[41] The industry trends were jointly significant. 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.

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 innovative UK industry in our sample, our results still hold, with a coefficient (standard error) on the key interaction term of 0.215 (0.068).[43]

4.3. Patent Citations Results

Our interpretation of our main results is that having inventors located in the US allows UK firms to access geographically localised spillovers. However, it is possible that the firm-level location weights are correlated with some unobserved firm-level characteristic that allows firms to absorb the information contained in spillovers from the US. As discussed above in section 4.2, we attempted to test for this using measures of absorptive capacity, firm quality, human capital and technological proximity. Recently, many authors have turned to patent citations as an alternative and direct way of measuring spillovers.[44] We use this alternative source of information as another way of investigating the possibility that our previous results are driven by unobserved heterogeneity, rather than geographic proximity.

To implement this approach we estimate a patent citation equation of the following form

$$CITES_{pit}^{US} = g(US_{pit}, UK_{pit}, W_i^{US}, W_i^{UK}, x_{pit}, u_{pit}). \tag{4.1}$$

[42] The coefficient on the interaction of US R&D and W_i^{US} in an equivalent specification to column (5) of Table 3 was equal to 0.191 with a standard error of 0.57.

[43] We also investigated including other countries R&D stocks (in addition to the US) and their interactions, but although usually positive these were rarely significantly different from zero, and their interactions with the relevant geographical location of the firm's inventors was never significant. This is not to say that the UK learns only from the US, rather that the US is by a long way the most important partner.

[44] For an early example see Adam Jaffe, Manuel Trajtenberg and Rebecca Henderson (1993).

The dependent variable $CITES^{US}_{pit}$ is a count of the number of non-self citations from patent p of UK firm i at time t to a patent with a US inventor that was applied for within the previous three years. This is the type of citation that we consider most likely to be associated with technology sourcing. US_{pit} and UK_{pit} are dummy variables that are equal to unity if the citing patent is invented in the US or UK respectively, and zero otherwise. The base category is all other countries. W_i^{US} and W_i^{UK} are the basic firm-level location weights described above. Control variables (x_{pit}) include the total number of cites made by the patent ($TOTALCITES_{pit}$), year dummies, industry dummies, technology class dummies and all other firm and industry-level variables in the production function.[45] Finally, u_{pit} is a serially uncorrelated error term.

An established result in the citations literature is that patents are more likely to cite other patents with inventors in the same country than they are to cite patents with foreign inventors, and these citations tend to come sooner.[46] Thus we expect US_{pit} to enter positively in equation (4.1). However, if our interpretation of the production function results is correct, we expect the firm-level variable W_i^{US} not to be significantly different from zero in equation (4.1) conditional on the location of the citing patent's inventor. If W_i^{US} were to enter positively, even after controlling for US_{pit}, this would suggest the presence of some firm-level propensity to cite US inventors that was not entirely accounted for by the presence of individual inventors in the US. In particular, it might be the case that the firm's UK-based inventors were also systematically more likely to cite US inventors. This would suggest that the firm-level location weight W_i^{US} was acting as a proxy for something more than just the geographical location of inventors in the US.

[45] The results were not very sensitive to the set of control variables that were included.

[46] See Adam Jaffe and Manuel Trajtenberg (2002) for a recent survey of this literature.

The sample is all patents applied for by our sample of UK firms over 1990-1998. Restricting our attention to patents applied for after 1989 allows us to use the same pre-sample firm-level location weights as before.[47] We estimate equation (4.1) by a negative binomial count data model.[48]

Table 5 presents the results. In column (1) we exclude the individual inventor location indicators US_{pit} and UK_{pit}. The firm-level location variable W_i^{US} is strongly associated with the propensity to cite US inventors. This initial result is reassuring as it corroborates the hypothesis that our firm-level inventor location weight is picking up knowledge transfers using a completely different methodology to the production function approach. If the US R&D labs of our UK firms were not really tapping into localised US knowledge (e.g. if they were just adapting European knowledge to the US market) we would not expect them to be extensively citing US patents.

In column (2) we include US_{pit} and UK_{pit} in the specification. The coefficient on the US inventor dummy is positive and highly significant, confirming the result found elsewhere in the literature that US inventors are more likely than foreign inventors to cite other US inventors. This is true even though all the patents in the sample are owned by UK firms. The reported coefficients on US_{pit} suggests that the citation rate per patent to US inventors is about 68% higher for patents invented in the US. More importantly for our purposes, conditioning on the location of the

[47] We do not consider patents applied for after 1998 because the patent database only contains information on granted patents. Since the process of granting a patent can take several years, this raises the possibility of truncation bias by omitting patents that have been applied for but not yet granted.

[48] Similar results to the Negative Binomial model emerge from a Poisson specification, although the Poisson model is strongly rejected in favour of over-dispersion. The data support a hypothesis of constant dispersion, with the additional dispersion coefficient, delta, significantly greater than zero, as shown in Table 4. We also estimated a probit regression where the dependent variable is equal to one if $CITES_{pit}^{US}$ is greater than zero, and the results were qualitatively very similar.

patent's inventor drives the coefficient on the firm-level location weight W_i^{US} to zero. So there is no evidence for any firm-level propensity to cite US inventors that is not entirely accounted for by the presence of individual inventors in the US. In particular, UK inventors are not more likely to cite US inventors when their firm's value of W_i^{US} is high.

These results from patent citation behaviour support our interpretation of the earlier production function results. UK firms with inventors located in the US are more able to benefit from localised 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.

5. 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 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 over 1990-2000 was associated with on average a 5% higher level of TFP for the UK firms in our sample. This compares with an average 6% higher level of TFP associated with the increase in their own R&D stocks over the same period.

The US innovation boom in 1990s had major benefits for the UK economy, and by implication for many other countries in the world. An interesting extension of our methods would be to replicate the findings for other countries. A larger stock of US R&D also increased 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 is driven by technology sourcing rather than other contemporaneous events.

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 recently expressed an aspiration to raise the level of R&D spending within the EU to 3% of GDP. One of the proposed ways of achieving this is through R&D tax credits. Evidence suggests that one of the main impacts of these is to encourage relocation of R&D.[49] Our results suggest that policies which seek to achieve this target by inducing multinational European firms to relocate their existing R&D efforts away from the US and towards Europe could be at least partly counterproductive, as they may reduce the ability of European firms to benefit from US R&D spillovers.

From the point of view of the US, 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. When it comes to international technology spillovers it seems there is no such thing as a completely free lunch.

[49] See Rachel Griffith and Nick Bloom (2001).

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A. Appendix: Data

In order to implement our empirical strategy we need to measure three types of information: the location of firms' innovative activity, firms' productivity performance, and the domestic and foreign spillover pools available to firms. We use data from the US Patent Office (USPTO), firm accounts data, and OECD data on industry level R&D expenditure.

A.1. Innovative activity

The first dataset is the NBER patent citations data file which contains computerised records of over two million patents granted by the USPTO between 1901 and 1999. This is the largest electronic patent dataset in the world. We restrict our attention to patents applied for after 1975 as data on citations are only available for patents applied for after this date. This is combined with firm accounting data from the Datastream on-line service which contains information on output, employment, investment, capital and R&D.[50]

A.1.1. Inventor location

Patents identify the address (including country) of the inventor(s) listed on the patent application. Table 1 (in the main text) shows the primary inventor's country for the 38,160 patents matched to our sample of 188 UK firms listed on the London Stock Exchange in 1985. The average share of a firm's patents with the lead inventor located in the US varies somewhat across industries, with the highest average share in Office, Accounting and Computing Machinery (47.5%), Radio, Television and Communication Equipment (47.2%) and Food, Beverages and Tobacco (46.4%), and the lowest shares in Textiles, Leather and Footwear (12.7%), Other Transport Equipment (24.5%) and Basic Metals (28.7%).

A.1.2. Patent Citations

We use data on patent citations to refine our measures of the location of firms' innovative activity. The 38,160 patents matched to our sample of UK firms make 275,013 citations to other patents, an average of 7.2 citations made by each patent. Of these 275,013 citations, 236,367 have information on the location of the lead inventor of the cited patent. Because we are interested in whether firms are benefitting from external knowledge that has not been generated within the same firm we exclude self-citations, where a patent cites another patent that is owned by the same firm. 8.5% of all citations in our sample are made to patents owned by the same patenting subsidiary (or "assignee"), while a further 1.4% of all citations are made to a different assignee that is nevertheless part of the same parent firm.

[50] More details of the matching between the datasets can be found in Nick Bloom and John Van Reenen (2002).

Table A1 shows a cross-tab of the location of the citing and cited inventor for the 209,090 non-self citations in our sample. It is important to remember that all of these citations were made by patents that are owned by UK firms, even if the inventor was located in the US. Only 6.9% of citations made *by* UK inventors are made *to* another UK inventor, while 59.9% are made to a US inventor. In contrast, 71.5% of citations made by US inventors are made to other US inventors, while only 3.2% are made to UK inventors. This probably illustrates both the fact that the data is from the US patent office, but also the dominant global position of the US in innovation. This provides preliminary evidence that most patents owned by UK firms, but invented by an inventor located in the US, are building on knowledge created by other inventors located in the US. When we look at self-citations to a patent that is owned by the same parent firm (not shown) the percentages in the diagonals (for example a UK inventor citing another UK inventor) are much higher. We also see that, even within firms, the transfer of knowledge from the UK to the US appears to be small compared to the transfer of knowledge within the US.

A.1.3. Patent Application dates

We also use information on the application dates of each citing and cited patent in order to refine our measures of the location of firms' innovative activity. In particular we look at citations made to patents that were applied for within the last three years. Table A2 shows the same cross-tab of the country of the citing and cited inventor for all non self-citations of this type. The proportions are similar to those in Table A1, although UK inventors are slightly more likely to cite other UK inventors than before, and US inventors are less likely than before to cite other US inventors.

A.2. Firm Accounts data

We sought to construct similar types of data for both US and UK firms, although some differences were inevitable. Both samples were independently matched to USPTO data. They are based on publicly listed firms, whose primary sales are in manufacturing and who report some R&D between 1990 and 2000. All data relates to the firms' consolidated worldwide accounts. Observations with missing data, firms with less than five consecutive observations over 1990 - 2000, and firms for which there were jumps greater than 150% in any of the key variables (capital, labour, sales) were dropped.

A.2.1. UK firms

For UK firms the data on value-added, labour (DS Item 219) and R&D expenditure (DS Item 119) comes from the Datastream On-Line service (DS) and is a sample of firms listed on the London Stock Exchange. Capital is estimated as a replacement value using the method described in Bond and Meghir (1994). 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 firms global activities. Value added is the sum of total employment costs (DS117), operating profits (DS137), depreciation (DS136) and interest payments (DS153).[51]

The initial sample is all firms listed on the LSE in 1985 with names starting with the letters A-L, plus any of the top 100 UK R&D performers not already included. The sample includes 415 firms, 266 of whom had taken out at least one patent between 1975 and 1998. All these firms' subsidiaries were identified using *Who Owns Whom* by Dun and Bradstreet in 1985.[52] Firms who entered the sample after 1985 were matched based on their date of entry. All the subsidiaries were then matched by name to the USPTO.

In the UK most firms did not report R&D expenditure before 1989 and so the analysis is restricted to the years 1990-2000.[53] An R&D capital stock was constructed using a perpetual inventory method and an assumed 15% rate of obsolescence (Griliches, 1979, and Hall et al, 2004).

Industry codes for UK firms are at the 3-digit level. We matched 3-digit SIC80 codes to 2-digit ISIC Revision 3 codes for the purposes of assigning firms to a 2-digit industry.

After cleaning our data we have a sample with 1794 observations on 188 firms, 141 of which are matched to at least one patent. Table 2 in the main text reports summary statistics. On average, firms in our sample have applied for 240 patents (see Table A3).

A.2.2. US firms

US Data was taken from the match between Compustat (CS) and the USPTO conducted by Bronwyn Hall et al (2000). We tried to make the sample and variable construction as close as possible to the UK sample. We matched in industry level data by primary SIC code (1987 Revision). The book value of capital is the net stock of property, plant and equipment (CS Item A8 - PPENT). R&D is CS item A46 - XRD. Unfortunately staff costs are only available for about 10% of firms in the Compustat data so constructing a value added measure is extremely difficult. Consequently we follow the tradition in the US literature (e.g. Griliches

[51] The first two items dominate this measure.

[52] As with other matches this has the disadvantage that we do not track changes in ownership over time. This is inevitable given the labor intensity of the data matching exercise. Another issue is that we do not track the sales of patents from one firm to another (this may cause us to overestimate the proportion of UK inventors in the US if UK firms buy many US patents). Fortunately such non-M&A related patent sales appear to be a relatively rare event.

[53] 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 sensitive to the exact treatment of reported zeros.

and Mairesse, 1998) and use real sales as our output measure (CS Item A12-SALE). Fortunately, using sales instead of value added in the UK leads to similar qualitative results to those for value added.[54]

The inventors of patents owned by US firms are much more localised in the United States than in UK firms (see Table 1). 95% of all inventors were located in the US and only about 1% of inventors were located in the UK. This reflects the innovative strength of the US and the fact we are using USPTO data, so there is some inevitable home bias for the US. The industries where there is greater US innovative presence in the UK are (unsurprisingly) those where the UK has some traditional strengths - medical equipment, pharmaceuticals, and petroleum refining. Table A4 describes the data on US firms.

A.3. Industry level data - R&D Spillover pool

The domestic and foreign spillover pools were constructed using the OECD's Analytical Business Expenditure on R&D dataset (ANBERD, 2002). This contains information on R&D spending at the 2-digit manufacturing industry (ISIC Revision 3) for all OECD countries. A stock measure was constructed using a perpetual inventory method and an assumed 15% rate of obsolescence,[55] 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 of the R&D activity. This would be extremely hard to recreate using data on firms' reported R&D as they do not decompose R&D into a foreign and domestic element. Our measure 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. We also use data on 2-digit industry level value-added taken from the OECD's Structural Analysis database (STAN, 2003). Value added price deflators at the two digit level are also used from this source. In addition, we use three digit value-added from the NBER productivity database and from the UK PACSTAT data (similar findings were uncovered from 3 and 2 digit analysis).

A.4. Technological Proximity Measure

We constructed a measure of technological proximity between our UK firms and US industries following the Jaffe(1986) method. We allocated the Compustat firms described above to a two digit industry and calculated the average technological profile using the average share of patents in each of the 623 technology classes in the USPTO. We the calculated the uncentered correlation coefficient between

[54] For example, in the context of our preferred model of column (5) of Table 3 the coefficient(standard error) on the key interaction term was 0.168 (0.083).

[55] We experimented with other depreciation rates but the results were not significantly changed.

each of our UK firms and the US industry. The technological proximity formula following Jaffe (1986) between firm i and industry, where firm i is in industry j, is

$$PROX_{ij} = \frac{T_i T_j'}{(T_i T_i')^{\frac{1}{2}} (T_j T_j')^{\frac{1}{2}}}$$

where $T_i = (T_{i1}, T_{i2}, ..., T_{i623})$ is a vector whose elements are the proportion of patents over the 1975 to 1989 period in each of 623 (labelled N-class) technology classes in the USPTO. $PROX_{ij}$ is the uncentered correlation. Compared to the original Jaffe (1986) paper and its descendents we are treating US industry j as a "pseudo" firm. We also tried an alternative measure using all patents among Compustat firms not distinguishing by industry.

B. Appendix: Econometric modelling strategy

In the main text we compare results from two alternative approaches to deal with these problems, a GMM method (Richard Blundell and Stephen Bond, 2000) and the popular "OP" method (Stephen Olley and Ariel Pakes, 1996) adapted for the presence of endogenous R&D (Thomas Buettner, 2004). These approaches are based on different assumptions and different strengths and weaknesses (see Griliches and Mairesse, 1998, for a discussion). The OP approach has a more flexible form for the "not so fixed" effect of the unobserved heterogeneity (allowing it to evolve over time as a Markov process). The GMM approach allows for a permanent component to unobserved heterogeneity and for the transitory component to be contemporaneously correlated with labour and capital. This appendix gives some more detail on each method.

B.1. System GMM

Consider a simplified form of the production function

$$y_{it} = \alpha x_{it} + a_{it} \tag{B.1}$$

where x_{it} is an endogenous input and the residual productivity term takes the form

$$a_{it} = t_t + \eta_i + u_{it}. \tag{B.2}$$

Year dummies (t_t) control for common macro effects and the firm fixed effect (η_i) and stochastic productivity shock (u_{it}) may be correlated with the regressors. Assuming no serial correlation in the u_{it} process yields the following moment conditions

$$E[x_{i,t-s} \Delta u_{it}] = 0 \tag{B.3}$$

for $s \geq 2$.[56] This allows the use of suitably lagged levels of the variables to be used as instruments after the equation has been first differenced. We test for serial correlation using an LM test, shown at the base of the GMM columns. If there is higher order (but finite) serial correlation in the u_{it} process longer lags can still be used as instruments.

Unfortunately, the first differenced GMM estimator has been found to have poor finite sample properties when the endogenous variables are highly persistent, because the lagged instruments are often weakly correlated with the first differences of the endogenous variables. If we are prepared to make assumptions on the initial condition that $\mathrm{E}[\Delta y_{i2}\eta_i] = 0$ and $\mathrm{E}[\Delta x_{it}\eta_i] = 0$ then additional moment conditions become available.[57] The additional moment conditions take the form:

$$E[\Delta x_{i,t-s}(\eta_i + u_{it})] = 0 \tag{B.4}$$

for $s = 1$ when $u_{it} \sim MA(0)$. This means that lagged differences of x can be used as instruments in the levels equations. We test the validity of the additional moment conditions using a Sargan difference test. The levels equations and differenced equations are stacked in a system, each with its appropriate instruments.

We assume that all firm-level variables are endogenous, whereas all industry-level variables are treated as exogenous. We examine specifications where the industry-level R&D stocks are treated as endogenous and the results are not significantly affected. The results are also robust to lagging the industry-level variables by one period, in which case they can be treated as pre-determined. 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.

The standard errors we present allows for arbitrary heteroskedasticity and arbitrary serial correlation. They are the "One-Step robust" results from the DPD package written in GAUSS[58] (i.e. we do not iterate on the GMM weight matrix because Monte Carlo evidence suggests this underestimates the second step standard errors). We include full sets of time dummies and industry dummies in all regressions.

B.2. Olley Pakes with endogenous R&D

Olley and Pakes (1996) essentially assume that the production function can be written

[56] If there is serial correlation in the error term this can be dealt with by using longer lags as instruments. For example, if $u_{it} \sim MA(1)$ lags dated t$-$3 and earlier will be valid instruments.

[57] Stationarity of y_{it} and x_{it} is sufficient (but not necessary) for these conditions to hold. What is essential is that the first moments of the endogenous variables are time invariant conditional on the time dummies. The higher order moments are unrestricted.

[58] Available from: http://www.ifs.org.uk/econometindex.shtml

$$y_{it} = \alpha_0 + \alpha_l l_{it} + \alpha_k k_{it} + \omega_{it} + \upsilon_{it} \quad \text{(B.5)}$$

where ω_{it} is the unobserved productivity state and υ_{it} is a serially uncorrelated additional productivity shock or measurement error (which can be serially correlated). This is equation (2.1) with $\beta = \gamma_{i1} = \gamma_{i2} = 0$ and $a_{it} = \omega_{it} + \upsilon_{it}$. Capital is quasi-fixed and labour completely variable. The bones of the Olley Pakes model is as follows. At the beginning of the period t, firm i observes its productivity state ω_{it} and capital stock k_{it}. The key difference between ω_{it} and υ_{it} is that ω_{it} is a state variable and affects investment decisions whereas υ_{it} does not. The firm decides whether to stay in business based on its expectations of net present value value compared to a critical cut off. Denote $\chi_{it} = 1$ if the firm chooses to stay in business and $\chi_{it} = 0$ if the firm chooses to exit. If the firm decides to continue operations it sets labour and chooses the level of investment in physical capital. Physical capital evolves in a deterministic process based on investment according to the standard perpetual inventory formula. The additional shock υ_{it} is then realized after these choices are made. The key insight of the OP algorithm is to use the monotonicity of the investment policy function in unobserved productivity (conditional on current capital). This can be used to get consistent estimates of the parameter on variable inputs at stage 1 and then use these (at stage 2) to obtain the capital coefficient.

We take two approached to dealing with firm R&D. First, we consider estimates of the standard OP algorithm and include R&D as an exogenous variable.[59] Secondly, we follow Thomas Buettner's (2004) extension of the OP structural model to include endogenous R&D chosen at the same time as fixed investment. Unlike fixed investment, however, R&D is stochastic. The productivity state ω_{it} still evolves stochastically over time according to a controlled Markov process, but the distribution of next period's productivity is increasing (in a first order stochastic dominance sense) not only in the current productivity state *but also in the amount of R&D expenditure.* We can think of this as the firm "buying" an improved probability distribution of ω_{it+1} through spending more on R&D this period.[60] We assume that the distribution of ω_{t+1} is governed by a parameter $\psi_{t,}$ a single index. The distribution of next period's productivity ω_{t+1} is a member of the family of distributions,

$$\digamma_{\psi_{t+1}} = \{F(\omega_{t+1}|\psi_{t+1}), \psi_{t+1} \in \Psi\}.$$

A contribution of Buettner (2003) is to show that (in the context of this extended structural model) the invertibility of the investment policy function still holds and that the R&D investment function is also invertible. Consequently

[59] Analogously to plant age in the original Olley Pakes (1996) application.

[60] This is an important restriction as it implies that R&D and ω_{it} affect ω_{it+1} only through $\psi_{it+1.}$ Thus productivity shocks and R&D are not allowed to have a qualitively different impact on the distribution of future productivity.

stage 1 of the OP algorithm does not need to be changed, although stage 2 must be altered to account for endogenous R&D.

B.2.1. Stage One: Estimation of the coefficient of the variable input.

The estimation strategy is to control for the unobserved productivity shock non-parametrically by exploiting the monotonicity of the investment policy function. Unobserved productivity can be written as[61]

$$\omega_{it} = \widetilde{\omega}(i_{it,} k_{it})$$

Substituting this into the production function (B.5) gives

$$y_{it} = \alpha_0 + \alpha_l l_{it} + \phi(i_{it,} k_{it}) + \upsilon_{it} \tag{B.6}$$

where

$$\phi_t = \phi(i_{it,} k_{it}) \equiv \alpha_0 + \alpha_k k_{it} + \widetilde{\omega}(i_{it,} k_{it})$$

We do not know the functional form of ϕ_t so we use a series estimator to approximate it.[62] Estimation of equation (B.6) gives a consistent estimate of α_l and estimates of the unknown function ϕ_t.

B.2.2. Stage Two: Estimation of the coefficient of the quasi-fixed input.

Rearranging (B.6) after we have an estimate of the coefficient on the variable input (α_l) gives

$$y^*_{it} = y_{it} - \alpha_l l_{it} = \alpha_0 + \alpha_k k_{it} + \upsilon_{it}$$

The expectation of y^*_{it}, conditional on information at $t-1$ and survival until t, is then

$$E[y^*_{it} | J_{t-1}, \chi_{it} = 1] = \alpha_0 + \alpha_k k_{it} + E[\omega_{it} | \psi_{it,} \chi_{it} = 1]$$

where J_{t-1} is the information set in $t-1$, and the distribution of productivity states is $\psi_{it,}$ (which is influenced by the firm's R&D choice). Under the Markov assumption for productivity, we can re-write productivity conditional on survival as:

$$\omega_{it} = E[\omega_{it} | \psi_{it,} \chi_{it} = 1] + \xi_{it}.$$

The second stage estimation becomes

$$y^*_{it} = \alpha_0 + \alpha_k k_{it} + E[\omega_{it} | \psi_{it,} \chi_{it} = 1] + \xi_{it} + \upsilon_{it}.$$

[61] Or equivalently $\widetilde{\omega}(k_{it+1,} k_{it})$ since capital is formed deterministically: $k_{it+1} = (1-\delta) k_{it}$.

[62] Olley and Pakes (1996) and Levinsohn and Petrin (2003) find that the fully non-parametric estimator of ϕ_t gives similar results to the series estimator. We found that fourth or sixth order series expansions (instead of our preferred fifth order) made little difference to the results.

where the productivity innovation ξ_{it} is uncorrelated with k_{it}.To control for selectivity we will take a similar approach to stage 1 and control for the expectation non-parametrically.

In the absence of selection[63] and R&D the second stage becomes simply

$$y_{it}^{*} = \alpha_0 + \alpha_k k_{it} + g(\omega_{it-1}) + \xi_{it} + \eta_{it} \tag{B.7}$$

Since $\omega_{it-1} = \phi_{t-1} - \alpha_k k_{it-1} - \alpha_0$, equation (B.7) can be estimated by non-linear least squares where the unknown function $g(\omega_{it-1})$ can be approximated by a nonparametric function in $\phi_{t-1} - \alpha_k k_{it-1}$.The key difference between Buettner's model and the original OP model is that $\psi_{it,}$ depends on both ω_{it-1} and k_{it-1} in the model with endogenous R&D whereas it only depends on ω_{it-1} in the original OP set-up. This means that there is a difference between the method we use to estimate stage 2 and OP.[64]

We use the fact that the R&D function can be written $r(\psi_{it,}\omega_{it-1})$ and invert this to obtain

$$\psi_{it} = r^{-1}(r_{it-1,}\omega_{it-1}) \tag{B.8}$$

where $r_{it-1,}$ denotes the observed R&D spend at t-1. Using equation (B.8) to control for the distribution in period t, the second stage estimation equation becomes

$$\begin{aligned} y_{it}^{*} &= \alpha_k k_{it} + g(r^{-1}(r_{it-1,}\omega_{it-1})) + \xi_{it} + \upsilon_{it} \\ &= \alpha_k k_{it} + \widetilde{g}(r_{it-1,}\phi_{t-1} - \alpha_k k_{it-1}) + \xi_{it} + \upsilon_{it} \end{aligned} \tag{B.9}$$

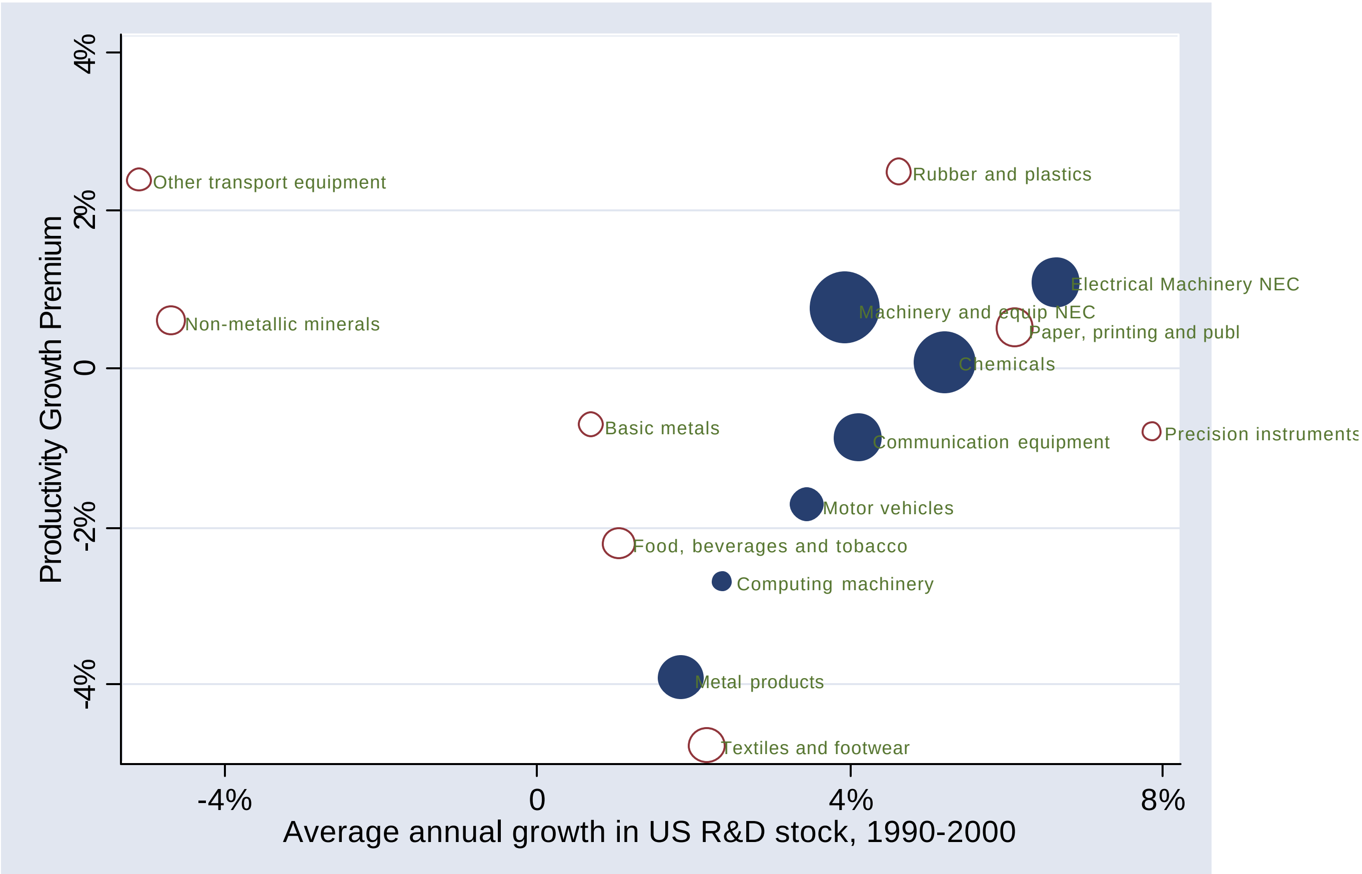
Equation (B.8) can be used to obtain estimates for α_k replacing $g(r^{-1}(.,.))$ with a nonparametric function $\widetilde{g}(.,.)$ in r_{it-1} and $\phi_{t-1} - \alpha_k k_{it-1}$.

Armed with these estimates for the parameters of the production function we can then construct the productivity term ω_{it}. Since the spillover terms are assumed exogenous they can be included as additional variables in the production function. We calculate the standard errors though a bootstrapping procedure with 100 replications.

[63] We allow for selection in the empirical results.

[64] In particular we cannot identify α_k from $g(\phi_{t-1} - \alpha_k k_{it-1}, k_{it-1})$.

Figure 1: US R&D growth and "productivity growth premium" for UK firms with a high proportion of US inventors



Notes: 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 labour 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. Although there is a positive relationship across all industries, it is strongest in the "high gap" sector.

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 our 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 the sample of 570 US firms. Final column refers to all patents registered at the US Patent Office between 1975 and 1998

Table 2: Descriptive Statistics for UK firms

	Mean	Median	Standard Deviation
Firm level variables			
Employees	10,711	1,750	27,564
Value added (£m)	372	48	914
Capital stock per worker (£)	38,700	30,000	31,900
Value added per employee (£)	31,404	50,201	12,438
R&D expenditure/value added	0.029	0.010	0.044
R&D stock/value added	0.158	0.046	0.272
Industry level variables			
Ln(UK R&D stock)	7.272	7.740	1.404
Ln(US R&D stock)	9.730	9.621	1.276

Notes: Sample includes 188 firms, 1990-2000; all monetary amounts are in 1995 currency, deflated using OECD 2 digit industry price deflator; firm level value-added is constructed as the sum of total employment costs, operating profit, depreciation and interest payments; capital stock and R&D stock are constructed using a perpetual inventory method as described in the text.

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)** $_{it}$
Company listed in:	**UK**	**UK**	**UK**	**UK**	**UK**	**UK**
Location weight: W_i	-	Location	Location	Location & Citation	Location & Citation within 3 years	Location & Citation within 3 years
ln (L/K) $_{it}$ labour-capital	-	0.657 (0.046)	0.648 (0.065)	0.647 (0.065)	0.642 (0.067)	-
ln (L) $_{it}$ labour	0.620 (0.057)	-	-	-	-	0.555 (0.039)
Ln(K) $_{it}$ capital	0.343 (0.042)	-	-	-	-	0.385 (0.041)
ln (R&D) $_{it,}$ firm R&D stock	0.029 (0.008)	0.012 (0.007)	0.026 (0.011)	0.025 (0.010)	0.022 (0.010)	0.015 (0.005)
W_i^{US} *** ln (US R&D)** $_{jt}$	-	0.076 (0.024)	0.066 (0.035)	0.084 (0.031)	0.173 (0.054)	0.165 (0.062)
W_i^{UK} *** ln (UK R&D)** $_{jt}$	-	0.035 (0.022)	0.026 (0.028)	0.092 (0.095)	0.400 (0.291)	-0.488 (0.557)
ln (US R&D) $_{jt}$ US industry R&D stock	-	0.050 (0.118)	0.065 (0.067)	0.059 (0.065)	0.063 (0.066)	-0.054 (0.038)
ln (UK R&D) $_{jt}$ UK industry R&D stock	-	0.273 (0.165)	0.221 (0.101)	0.219 (0.101)	0.206 (0.096)	0.250 (0.083)
W_i^{US} % inventors in US	-	-0.696 (0.240)	-0.602 (0.336)	-0.765 (0.313)	-1.658 (0.543)	-1.353 (0.617)
W_i^{UK} % inventors in UK	-	-0.296 (0.156)	-0.254 (0.193)	-0.760 (0.683)	-3.270 (2.533)	3.127 (4.336)
Firms	188	188	188	188	188	188
Observations	1794	1794	1794	1794	1794	1794
1st order serial correlation test *(p-value)*	-	-	-1.212 *(0.226)*	-1.212 *(0.226)*	-1.212 *(0.225)*	-
2nd order serial correlation *(p-value)*	-	-	-1.788 *(0.074)*	-1.769 *(0.077)*	-1.719 *(0.086)*	-
Sargan Difference Test *(p-value)*	-	-	17.52 *(0.562)*	17.90 *(0.534)*	18.81 *(0.456)*	-
Sargan Test of over-identifying restrictions *(p-value)*	-	-	86.39 *(0.217)*	86.18 *(0.222)*	86.52 *(0.214)*	-

Notes: W_i^{US} and W_i^{UK} are the (pre-1990) proportion of a firm's inventors located in the US and UK respectively. Standard errors in brackets under coefficients 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 System-GMM (one-step robust standard errors). In System GMM (see Blundell and Bond, 2000) the firm-level variables are assumed endogenous and industry level 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-Pakes, 1996). In OP we use a fifth order series expansion in the first and second stage (the second stage also includes a selection correction term). After obtaining the firm specific (total factor) productivity term (**?** $_{it}$) from stage one, we regress this against the indicated variables (including full sets of industry and time dummies). In OP the standard errors are bootstrapped (100 replications) and allow for clustering by firm. For diagnostic tests p-values are in brackets and italics. All equations include a full set of industry dummies and time dummies.

Table 4: R&D Augmented Production Function results – Further Investigations

	(1)	(2)	(3)	(4)
Estimation method	**GMM**	**GMM**	**GMM**	**GMM**
Dependent variable	**ln (Y)** $_{it}$	**Log(Y/K)** $_{it}$	**Log(Y/K)** $_{it}$	**Log(Y/K)** $_{it}$
Company listed in	**USA**	**UK**	**UK**	**UK**
Sample	**USA**	**High TFP Gap with USA**	**Low Gap with the USA**	**"Domestic"**
Location weight:	Location	Location & Citation within 3 years	Location & Citation within 3 years	Location & Citation within 3 years
ln (L/K) $_{it}$	-	0.757 (0.076)	0.518 (0.087)	0.610 (0.072
ln (L) $_{it}$	0.706 (0.078)	-	-	-
ln (K) $_{it}$	0.220 (0.052)	-	-	-
ln (R&D) $_{it}$	0.049 (0.035)	0.029 (0.013)	0.005 (0.014)	0.029 (0.014)
W_i^{US} *** ln (US R&D)** $_{jt}$	0.002 (0.072)	0.277 (0.130)	0.123 (0.093)	0.212 (0.063
W_i^{UK} *** ln (UK R&D)** $_{jt}$	0.151 (0.131)	0.434 (0.267)	-0.826 (1.072)	-0.672 (0.408
ln (US R&D) $_{jt}$	0.247 (0.078)	0.353 (0.171)	0.035 (0.070)	0.116 (0.096
ln (UK R&D) $_{jt}$	-0.063 (0.046)	0.404 (0.152)	-0.041 (0.121)	0.211 (0.115
W_i^{US}	-1.244 (0.978)	-2.849 (1.445)	-1.182 (0.844)	-2.028 (0.637)
W_i^{UK}	-0.097 (0.781)	-3.540 (2.338)	4.861 (7.040)	4.199 (2.757)
Firms	570	99	89	135
Observations	5446	938	856	1267
1st order serial correlation test *(p-value)*	*-4.877* *(0.000)*	-1.101 (0.271)	-2.702 (0.007)	-1.198 (0.231)
2nd order serial correlation *(p-value)*	-1.739 *(0.082)*	-0.243 (0.808)	-1.468 (0.142)	-1.814 (0.070)
Sargan Difference Test *(p-value)*	*39.34* *(0.063)*	10.84 (0.941)	21.22 (0.336)	13.99 (0.693)
Sargan Test of over-identifying restrictions *(p-value)*	67.96 *(0.081)*	55.22 (0.801)	66.93 (0.197)	83.63 (0.283)

Notes: Column (1) contains US firms and columns (2) through (4) contain UK firms. "High TFP Gap" indicates those industries where the TFP gap with the USA was above the median (see Figure 1). "Domestic" indicates the sub-sample of UK firms who are estimated to have little or no overseas production facilities. W_i^{US} and W_i^{UK} are the (pre-1990) proportion of a firm's inventors located in the US and UK respectively. Standard errors in brackets under coefficients are robust to heteroskedacity and autocorrelation of unknown form. The dependent variable in columns (2) through (4) is the log of value added divided by capital stock and in column (1) it is the log of real sales. The time period is 1990-2000. All columns are estimated by System-GMM (one-step robust standard errors). The firm-level variables are assumed endogenous and industry level 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. For diagnostic tests p-values are in brackets and italics. All equations include a full set of industry dummies and time dummies. Column (1) also includes US industry value added (which was insignificant in the other columns) to control for domestic industry-level shocks.

Table 5: Citations results

	(1)	(2)
Dependent variable	$CITES_{pit}^{US}$	$CITES_{pit}^{US}$
W_i^{US}	0.631	0.104
	(0.267)	(0.198)
W_i^{UK}	0.197	0.054
	(0.205)	(0.199)
US_{pit}	-	0.684
		(0.158)
UK_{pit}	-	0.037
		(0.107)
$TOTALCITES_{pit}$	0.013	0.012
	(0.001)	(0.001)
Dispersion (delta)	1.050	0.999
	(0.069)	(0.067)
Observations	14,161	14,161
Mean of dep. var.	0.695	0.695
Log Pseudo-L	-15,116.06	-14,996.25

Notes: Estimated using a negative binomial count data model with constant dispersion. The dependent variable is the number of citations per patent to a US inventor (not owned by the same firm and applied for within the last three years). The sample consists of all patents applied for by our UK firms between 1990 and 1998. Reported coefficients are equal to the incidence-rate ratio minus one. W_i^{US} and W_i^{UK} are the (pre-1990) proportion of a firm's inventors located in the US and UK respectively. US_{pit} and UK_{pit} denote whether the patent's lead inventor is located in the US or UK respectively. *TOTALCITES* is the total number of cites made by the patent. Robust standard errors in brackets are adjusted for clustering by firm. All specifications include 8 year dummies, 14 industry dummies and 36 technology class dummies, as well as all firm and industry level variables from the production function in Table 3.

Appendix Tables

Table A1: Location of citing and cited inventors: non self-citations

Cited country:	UK	USA	Other	Total
Citing country:				
UK	3,978	34,762	19,332	58.072
	(6.9%)	(59.9%)	(33.3%)	(100%)
USA	3,375	75,249	26,570	105,194
	(3.2%)	(71.5%)	(25.3%)	(100%)
Other	1,463	24,431	19,930	45,824
	(3.2%)	(53.3%)	(43.5%)	(100%)
Total	8,816	134,442	65,832	209,090
	(4.2%)	(64.3%)	(31.5%)	(100%)

Notes: all citations made by patents matched to the 188 UK firms in our sample, excluding self-citations (where the citing and cited patent are matched to the same parent firm). The time period is 1975-1998.

Table A2: Location of citing and cited inventors: non self-citations to patents that have been applied for within the previous three years

Cited country:	UK	USA	Other	Total
Citing country:				
UK	817	5,886	4,549	11,252
	(7.3%)	(52.3%)	(40.4%)	(100%)
USA	459	10,905	4,561	15,925
	(2.9%)	(68.5%)	(28.6%)	(100%)
Other	256	4,242	4,828	9,326
	(2.7%)	(45.5%)	(51.8%)	(100%)
Total	1,532	21,033	13,938	36,503
	(4.2%)	(57.6%)	(38.2%)	(100%)

Notes: all citations made by patents matched to the 188 UK firms in our sample to other patents that have been applied for within the previous three years, excluding self-citations (where the citing and cited patent are matched to the same parent firm). The time period is 1975-1998.

Table A3: Summary statistics for UK patenting firms

	Mean	Median	Standard Deviation	Min	Max
Total patent applications	240	40.5	657	1	5820
UK Location Weight	0.354	0.274	0.363	0	1
UK Location + Citation Weight	0.082	0.017	0.145	0	1
UK Location + Citation Within 3 Years	0.019	0.000	0.054	0	0.5
USA Location Weight	0.462	0.425	0.379	0	1
USA Location + Citation Weight	0.417	0.368	0.349	0	1
USA Location + Citation Within 3 Years	0.162	0.134	0.184	0	1

Notes: 141out of our 188 UK firms matched to at least one patent; location weights are constructed as described in the text.

Table A4 Descriptive Statistics for US firms

	Mean	Median	Standard Deviation
Employees	13,760	3,528	38,640
Real Sales ($1000)	3,196	586.4	10,742
Capital per employee ($)	59,407	34,607	81,630
Real sales per employee ($1000s)	193.736	162.843	128.641
R&D expenditure/value added	0.059	0.029	.198
R&D stock/value added	0.237	0.113	0.567

Notes: All in 1995 prices, 570 firms, 5446 observations, 1990-2000

Table A5: Data underlying Figure 1

Industry	Average annual % Growth in US R&D stock	R&D expenditure /Value added in US in 2000 %	Mean annual labour productivity growth for high W^{US} firms (%)	Mean annual labour productivity growth for low W^{US} firms (%)	Difference in mean annual labour productivity growth rate	Observations in UK sample	Observations in US sample
High US-UK TFP gap industries							
31 Electrical Machinery NEC	6.65	10.1	5.76	4.67	1.08	143	354
24 Chemicals (including pharmaceuticals)	5.23	13.2	5.81	5.73	0.07	191	820
32 Communication equipment	4.13	19.4	5.27	6.16	-0.88	138	725
29 Machinery and equip NEC	3.96	5.8	-0.94	-1.70	0.76	277	659
34 Motor vehicles	3.48	16.1	2.31	4.05	-1.73	63	264
30 Computing machinery	2.39	32.1	2.47	5.18	-2.71	20	323
28 Metal products	1.85	1.9	-2.89	1.03	-3.92	104	268
Low US-UK TFP gap industries							
33 Precision instruments	7.88	31.6	5.11	5.91	-0.80	58	696
20-22 Paper, printing and publishing	6.12	1.6	1.05	0.54	0.50	170	607
27 Basic metals	0.71	1.3	4.28	5.01	-0.72	80	168
25 Rubber and plastics	4.64	3	1.53	-0.95	2.48	72	347
17-19 Textiles and footwear	2.19	0.5	-2.67	2.08	-4.76	174	261
15-16 Food, beverages and tobacco	1.07	1.1	0.87	3.09	-2.21	131	283
35 Other transport equipment	-5.08	18.3	7.10	4.69	2.40	73	109
26 Non-metallic minerals	-4.66	2.3	0.97	0.36	0.61	98	132

Notes: TFP is calculated based on a superlative index. Labour productivity is real value added per worker.
US R&D stock is calculated using a perpetual inventory method and a 15% rate of obsolescence.

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