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What are the Channels for Technology Sourcing? Panel Data Evidence from German Companies

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Abstract

Innovation processes within corporations increasingly tap into international technology sources, yet little is known about the relative contribution of different types of innovation channels. We investigate the effectiveness of different types of international technology sourcing activities using survey information on German companies complemented with information from the European Patent Office. German firms with inventors based in the US disproportionately benefit from R&D knowledge located in the US. The positive influence on total factor productivity is larger if the research of the inventors results in co-applications of patents with US companies. Moreover, research cooperation with American suppliers also enables German firms to better tap into US R&D, but cooperation with customers and competitors does not appear to aid technology sourcing. The results suggest that the "brain drain" to the US can have upsides for corporations tapping into American know-how.

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1 Introduction

A number of recent contributions have shown that since the 1980s, R&D and innovation processes have become increasingly internationalized. While R&D used to be considered a typical headquarter activity in the decades after WWII, most multinational firms nowadays utilize several R&D locations in order to tap into the knowledge that is available in particular countries and regions[1]. Policy-makers are still trying to grapple with this development – after all, the build-up of R&D capacities abroad may weaken domestic R&D activities, and the international connections of multinationals (MNEs) may also lead to other countries profiting from any R&D subsidies that domestic firms receive. Hence, it is of considerable importance to gauge the implications of the globalization of R&D and innovation.

Moreover, for the last decade management researchers have shown that commercial innovation processes are veering towards an "open innovation" approach whereby innovating firms rely increasingly on contributions by external partners, both international and national (Chesbrough, 2003). But while the tendency towards more distributed innovation processes has been documented in recent studies (e.g. Laursen and Salter, 2006), little systematic evidence is available to demonstrate that "open innovation" has had a major impact on firm level outcomes. For corporate decision-makers it is also important to measure the impact of different forms of opening the innovation processes. Which forms of collaboration and technology sourcing provide a particularly strong impact on productivity?

Our paper addresses this issue which is at the intersection of the economics and management of innovation processes. While earlier work has employed patent data, we rely on a unique combination of survey-based firm-level information on modes of cooperation and technology sourcing with publicly available patent data.

Much of the literature on R&D internationalization rests on the notion of R&D externalities. Due to the public good property of knowledge, companies can benefit from knowledge created by other parties, even if the research is undertaken at distant locations. However, there are geographic boundaries to knowledge spillovers.[2] Since some parts of knowledge are tacit and can best be accessed through face to face interactions, knowledge can be described as local public good.

In order to gain access to tacit knowledge, companies may need a local presence in the proximity of and access to the knowledge source. Therefore, it can be useful for companies to locate R&D activities abroad. Technology sourcing can be defined as sourcing technological knowledge from local knowledge pools. This paper examines whether companies that have inventors based in a different country or have R&D cooperations in other countries benefit more from the foreign knowledge stock. In this regard it follows a number of other studies. Griffith et al. (2006) investigate whether UK firms with inventors based in the USA benefit from the knowledge available in this country. The authors find evidence that basing inventors abroad is an effective strategy for technology sourcing. Their analysis focuses on companies from the UK and employs patent data from the USPTO.

Papers in this tradition may be criticized on the ground that publicly available data do not contain detailed information on firm-level collaboration. The presumed externalities detected when using patent data may be caused in part by commercial relationships in which external partners simply provide research results and knowledge as an input. In this paper, we therefore extend the analysis by investigating the impact of inventor location as well as co-applications which indicate the presence of formal collaborations. Moreover, we explicitly consider different modes of collaboration, such as R&D cooperations with customers, suppliers, and competitors.

Distinguishing between different forms of technology sourcing allows us to contribute to the managerial literature on innovation management and open innovation. So far the mechanisms of technology sourcing are not well understood. There are important differences with respect to the intensity of exchange with local researchers and corporations. Companies can locate researchers abroad or they can have researchers work together with foreign companies resulting in co-applications of patents. There are also differences with respect to how technologically advanced R&D activities at the location of the collaboration are. For example, companies may aim at adapting existing products to new markets, or they may pursue the more ambitious objective of developing new technologies at the foreign location.

To identify the various mechanisms leading to productivity growth, our analysis employs data from the Mannheim Innovation Panel (MIP). The panel dataset we use covers more than 900 German companies over the time period from 1992 to 2003. The MIP data contain information on whether companies engage in R&D cooperation in foreign countries and whether these cooperations involve customers, suppliers, or competitors. Information on inventor location is taken from patent applications to the European Patent Office (EPO). The knowledge stock abroad is approximated with business R&D expenditures at the sectoral level (OECD’s ANBERD). We focus on R&D activities of German companies in the USA, since in many areas the USA is the technologically most advanced country. Moreover, given the size of the US economy, the US is also an attractive location for R&D that seeks to adapt products to the needs of US customers.

The information on the intensity of exchange with local researchers is calculated from patent data. Since the private address of inventors is given, we know whether German companies have inventors in the US. Some German companies apply for patents together with US companies (co-patenting), which is an indication of formal collaboration in research and development. We infer how technologically advanced the US-based R&D activity is from the type of cooperation partner. Cooperations with customers are often entered into in order to adapt existing products to new markets. Cooperations with competitors or suppliers more likely have the aim of developing new technologies. We estimate a Cobb-Douglas production function augmented with external knowledge stocks. The activities of technology sourcing are interacted with the external knowledge stocks. The coefficients of the interaction terms allow us to assess the extent to which companies benefit from technology sourcing in the form of higher TFP.

We find evidence that those differences in the type of the R&D activity matter. It is important how close contacts are, and closer contacts are better for technology sourcing. Companies benefit from having inventors based in the US. However, companies benefit more if they are engaged in joint R&D projects with local companies that results in joint patent applications. The type of cooperation partner matters as well. We find evidence for a positive influence of cooperation with suppliers on TFP. For cooperations with customers and competitors we find no influence.

The findings have implications for economic policy and for managerial decision-making. Our results clearly indicate that overall company performance profits from undertaking R&D in foreign locations. While this result is not surprising, it should be helpful in answering concerns of the policy-making community. Encouraging cooperation with foreign partners may even be useful in order to advance domestic productivity.

The remainder of the paper presents our approach, data and results. Section 2 describes the theoretical framework and develops our hypotheses. Section 3 presents the empirical model and data. Section 4 presents the empirical results, and Section 5 concludes.

2 Theoretical Framework and Hypotheses

Our paper seeks to contribute to the literature on technology sourcing and international R&D-related knowledge flows. Moreover, we shed light on the questions which modes of cooperation are particularly productive when firms seek to open their innovation processes for contributions of collaborating entities. We draw on these literatures to develop our hypotheses.

There is a large literature on knowledge spillovers. One strand focuses on domestic spillovers (see, for example, Harhoff, 2000; Bloom et al., 2010 on spillovers and product market rivalry). Another strand focuses on international spillovers. International economics investigates knowledge spillovers working through trade and foreign direct investment. International spillovers are analyzed by, for example, Coe and Helpman (1995). Keller (2004) provides a literature review on international technology diffusion.

Access to the part of knowledge that is codified is likely to be insensitive to geographical distance. No matter where the researcher is located, the information regarding this form of knowledge has the same quality. But it is also well established that knowledge flows are geographically bounded (e.g. see Griffith et al. for recent evidence). Since some parts of knowledge are tacit and can best be accessed through face to face interactions, knowledge can be described as local public good. In order to gain access to tacit knowledge, companies need a local presence in the proximity of and access to the knowledge source.

Since it is often not possible or not efficient to create all knowledge necessary for the development of a specific product inside the company, it has become increasingly important for firms to tap into knowledge that is available outside the own boundaries. Due to the "tacitness" of some part of knowledge, companies need to interact with other researchers that are outside the own country. The ascendancy of "open innovation" processes has made it all the more important for firms to seek out and utilize external providers of innovation-related information.

FDI is an important channel for overcoming the geographic boundedness of knowledge spillovers. Branstetter (2006) shows that Japanese multinationals undertaking direct investments in the USA enjoy productivity advantages in comparison to firms without this FDI activity.[3] In a similar vein, Iwasa and Odagiri (2004) look at knowledge sourcing by Japanese companies in the US. Research-oriented subsidiaries of Japanese firms in the US benefit from locally available knowledge.

Firms may also engage in formal collaboration with particular partners who possess specific forms of knowledge. The knowledge flows in such collaborations need to be distinguished from externalities, since they are likely to be governed by a commercial quid pro quo. The collaborating partners will engage in a contractual relationship, and information flows are likely to be accompanied by payments made by the net receiver of knowledge. We build in particular on an earlier contribution by Cassiman and Veugelers (2002) who point out that the mechanisms of technology sourcing have not been the subject of detailed scientific studies. While they focus on a limited set of sourcing modes, we investigate several mechanisms, such as formal cooperation with customers, suppliers and competitors.

We look at mechanisms for technology sourcing that can be achieved with existing employees. Complementary research looks at the hiring of experienced researchers from competitors as a further strategy of knowledge acquisition (see, for example, Almeida and Kogut, 1999 and Singh and Agrawal, 2011).

In this paper we want to shed light on the question of how successful different types of R&D activity abroad are for technology sourcing. One main strategy is to locate own researchers abroad. In this way the researchers are closer to the knowledge of other countries. The intensity of interaction with local researchers can differ. It is possible that researchers mainly work alone but have informal contacts to other researchers, or alternatively, it is possible that researchers work together with other companies on joint research projects. In this paper we will look at both forms of R&D activity abroad. Cockburn and Henderson (1998) show that the research productivity of pharmaceutical firms is higher if the firms have a higher share of their publications coauthored with universities. The process of preparing joint publications requires close collaboration and leads to an exchange of tacit knowledge.

Other studies have shown that research collaborations as documented by co-inventions support the transmission of knowledge (Breschi and Lissoni, 2006; Jaffe et al., 2000 and Singh, 2005). Such individual-level collaborations may be initiated within formal R&D cooperations. Companies have the possibility to cooperate with different partners abroad. The most common partners are customers, suppliers and competitors. Independent of where the cooperation partner is located, companies benefit from R&D cooperations through cost and risk sharing, by avoiding duplication of effort, cross-fertilization of ideas, shortening development times, and access to specific knowledge of the partner (Hagedoorn, 1993). A large literature has analyzed the determinants of R&D cooperations (see, for example, Cassiman and Veugelers, 2002; Hernan et al., 2003; Röller et al., 2007; Sakakibara, 1997; Belderbos et al., 2004a; and Kaiser, 2002). Astonishingly little is known about the impact of R&D cooperations on firm-level productivity (see, for example, Belderbos et al., 2004b).

In this paper we investigate whether collaboration with particular types of cooperation partners are a means of successful technology sourcing. Different cooperation partners typically imply differences in the type of joint activities. First, collaborations with customers often have the aim of adapting existing products to new markets. The development of new technologies is not at the forefront of interests. Companies have the opportunity to learn about the demand and the preferences of customers and to adapt products to local tastes (von

Hippel, 1988). Second, companies can get access to upstream technological developments in cooperations with suppliers. Typically, the R&D activity involved in this form of cooperation would be technologically more advanced than in cooperations with customers. Cooperations with suppliers are, for example, very important in the German automotive industry (Felli et al., 2011). Third, companies can cooperate at pre-competitive stages of technology development with competitors. Cooperations with competitors can be beneficial, because competitors often face the same problems. Furthermore, companies can learn about the strengths and weaknesses of competitors in cooperations. These cooperations give the opportunity to develop common standards, to influence the regulatory environment and to share development costs (Röller et al., 2007).

3 Empirical model and Data

3.1 Empirical Specification

We estimate a Cobb-Douglas production function which is augmented with external knowledge stocks (Griliches, 1992 and Griffith et al., 2006).

$$\begin{aligned} ln\ sales_{it} = {} & \beta_1\ ln\ employment_{it} + \beta_2\ ln\ materials_{it} + \beta_3\ ln\ capital_{it} \\ & + \beta_4\ ln\ firm\ R\&D_{it} + \beta_5\ dummy\ zero\ firm\ R\&D_{it} \\ & + \beta_6\ ln\ US\ industry\ R\&D_{jt} + \beta_7\ ln\ GER\ industry\ R\&D_{jt} \\ & + \beta_8\ w_{iUS} * ln\ US\ industry\ R\&D_{jt} + \beta_9\ w_{iGER} * ln\ GER\ industry\ R\&D_{jt} \\ & + \beta_{10}\ ln\ US\ industry\ value\ added_{jt} + \beta_{11}\ ln\ GER\ industry\ value\ added_{jt} + \mu_i + \varepsilon_{it} \end{aligned}$$

Where $R\&D_{it}$ is the stock of R&D in company i at time t and subscript j indicates industry-specific information. w_{iUS} is the company-specific spillover weight which indicates the type of

R&D activity that is performed in the US and w_{iGER} is the equivalent measure for Germany (see below for exact definitions). In the case of the patent-related variables, the intensity of the activity is reflected as well. A "US" pre-fix denotes US based activities and a "GER" prefix denotes German based activities.

The coefficient of main interest is β_8. It is the coefficient on the interaction term between the US knowledge stock and the "exposure" of the German company to this knowledge. A positive and significant coefficient would indicate that German companies successfully source knowledge in the USA. Note that the weights $w_{iCOUNTRY}$ are time invariant and thus absorbed by the firm fixed effect. The identification of β_8 comes from the differential impact of (time-varying) industry R&D on the (time-invariant) exposure of the firm to US (or German) ideas as proxied by the type of R&D activity conducted in the US (or Germany). It is analogous to a difference in differences method where the first difference is the change in industry by country R&D and the other difference is across firms (within an industry) which employ more or fewer inventors located in a particular nation.

An industry-level measure of value added is included to control for industry-level shocks that may be correlated with R&D activity. Company fixed effects (μ_i) and year dummies are included in all specifications. Because the company-specific spillover weight is time-invariant, its basis term is eliminated by the fixed-effects approach.

The term ε_{it} is a stochastic error term. Since this may be correlated with contemporaneous values of the factor inputs we also present GMM models where we allow for endogeneity and instrument the first differenced version of the production function with lags of variables dated t-2 and before (Arellano and Bond, 1991). We also considered the additional moments in Blundell and Bond (1998), but found that these were generally rejected by specification tests. In any case we did not find a large downward bias on the capital coefficient often found in production function estimates.

The weights we use are time invariant and the patent-based weights are averaged over the long time period of 1978 to 2003. Since the post 1993 data may be contaminated by endogeneity we consider robustness tests using only pre-sample 1993 values of the patent-based weights to assess the magnitude of any suspected bias. Unfortunately, the time-dimension in our data is not long enough to allow us the use of pre-sample information for the cooperation partners.

We consider a GMM approach following Blundell and Bond (2000) rather than a control function approach to estimate the firm-level production functions. Including another endogenous state variable (which affected the evolution of productivity) into a control function framework such as the one of Olley and Pakes (1997) is non-trivial (see the discussion in Ackerberg et al. (2007) for example). This is because the dynamic structural model underlying the approach has to be re-solved. The approach developed by Doraszelski and Jamandreu (2008) is a one attempt but does rely on some rather strong assumptions about competition in the factor input markets. The attraction of the GMM approach is that all factor inputs chosen at the firm-level are treated in the same way as endogenous variables.

3.2 Data Sources

3.2.1 Survey data

Our analysis is based on the Mannheim Innovation Panel (MIP), an annual survey providing information about German companies with at least five employees. The survey includes detailed information about R&D activities as well as basic company characteristics. The survey methodology largely follows the guidelines of the OECD/Eurostat Oslo-Manual on innovation statistics. The MIP is a voluntary mail survey with a response rate of between 20 and 25 percent. The first wave of the Mannheim Innovation Panel (MIP) was carried out in

1993. Every fourth year the survey is the German part of the European wide Community Innovation Surveys (CIS) coordinated by Eurostat (1993, 1997 and 2001).

The target population of the MIP covers legally independent German firms. Since there is no business register in Germany, a private information source is used for the sampling frame. The sampling frame is the database of Germany’s most important credit rating agency ‘Creditreform’ from which a stratified random sample is drawn. Stratification is done according to eight size classes, industry (mostly according to 2-digit NACE classes) and region (East and West Germany). A sample refreshment takes place every second year.

The MIP covers companies from the manufacturing and the service sector, but we limit our analysis to companies from manufacturing, as industry-level data on R&D expenditures in services are very limited. We use an unbalanced panel covering the years 1992 to 2003. Only companies with at least five consecutive observations are included. Companies belonging to a non-European group (e.g. head-quartered in the US or in Japan) are excluded. The analysis is based on 6447 observations of 910 companies.

3.2.2 Patent data

The information from the MIP is combined with patent information from the European Patent Office (EPO). Information on all patent applications since 1978 is available. For companies belonging to a group the ultimate owner has been identified. Patent information for the ultimate owner and all its subsidiaries is used for companies belonging to a group. The inventor location is identified from patent applications to the European Patent Office (EPO). Information on applications is taken from ESPACE Bulletin, a data base published by the EPO, which contains full information on patent applications for the years 1978 to 2003. The patent data is matched to the company data through a comparison of name and address information of companies and applicants. Matches are suggested by a text search algorithm and then manually checked.

The information on patents applied for by groups is taken from the CEP/IFS merge of EPO patents with European companies (Abramovsky et al., 2008). Information on the ownership structure of companies from the Amadeus data base was used to determine the ultimate owner for companies belonging to a group. Ownership shares of 50 percent or more are followed upwards until the ultimate owner is found. All European subsidiaries covered in Amadeus and belonging to the ultimate owner are included in the group structure. The patent holdings of the ultimate owner and all European subsidiaries are used for sample companies belonging to a group. The ownership information from the year 2005 is the basis for the construction of the ultimate owner.

3.2.3 Industry-level data

The company level data is completed with industry information from the OECD for Germany and the USA. Industry-level R&D information is taken from the OECD source ANBERD. It contains business R&D expenditure at the two-digit SIC level. The analysis is limited to the manufacturing sector and to the years 1992-2003 due to restrictions in this data source. The OECD STAN database is used to obtain information on industry specific value added as a volume index at the two-digit SIC level.

Our analysis focuses on R&D activities of German firms in the USA. We chose the USA, since this country plays a leading role in many high-tech sectors. Since US companies are often at the forefront of technological developments, they are attractive partners for technology sourcing. The attractiveness of North American research partners has increased over time. The share of research partnerships between Europe and North America in all research partnerships has increased from 16.2% in the 1960's to 25.2% in the 1990's

(Hagedoorn, 2002). This is an indication that the costs of such partnerships have fallen or that the rewards have increased.

3.3 Computation of Variables

The input variables turnover, material costs, capital stock and R&D stock are deflated to 1995 prices.[4] Labor input is measured as number of employees in full-time equivalents. The capital stock of the company is calculated using the perpetual inventory method. Tangible assets are taken as starting value for the capital stock, we use depreciation rate of 15%.[5] The perpetual inventory method is also used to calculate the R&D stocks at company and industry level (using ANBERD) from R&D expenditures with the same assumptions on depreciation and steady state growth as other capital.

Information on inventor location in EPO patent applications is used to identify whether companies have inventors based in the USA. We calculate the share of patents with at least one inventor based in the USA as an indicator of the importance of technology sourcing activity (% Inventors). The calculation of the time-invariant weights is based on the full patent application stock of the firms during the time-period from 1978 to 2003. An analogous variable is calculated for inventors based in Germany. The EPO does not indicate a lead inventor in patent applications, therefore all inventors are considered. We also calculate the share of patent applications with a US company as Co-applicant and an analogous variable for Co-applications with other German companies (% Co-applicants). Co-applications with companies in the USA or in Germany belonging to the same group as the MIP company are disregarded for the calculation of this measure. We use the patent stock of the companies in the year 2003 as basis for the calculation of the patent-related variables. The patent related variables are set to zero for companies without patent applications[6].

Information on cooperations is taken from the MIP. R&D cooperation is defined in the survey as active participation in joint R&D projects with other companies or not-for-profit organizations. Mere contract research without active collaboration is not counted as cooperation. The time-invariant dummy variable for R&D cooperation is set equal to one if the company indicated in at least one MIP survey that it engaged in R&D cooperation with a company in the USA or Germany respectively. Information on cooperation was collected in the years 1993, 1997 and 2001 and covers the time periods 1992, 1994-1996, and 1998-2000. The survey questions referred to R&D cooperation in the year 1993 and to innovation cooperation in the remaining years.

It is possible to differentiate different forms of cooperation according to partner. We look separately at cooperation with customers, suppliers, and competitors. Information on the type of cooperation partner as well as on the country where the cooperation partner resides is extracted from the MIP data.[7]

4 Empirical Results

4.1 Descriptive Statistics

Table 1 contains descriptive statistics for the productivity variables. Our sample contains mainly medium-sized companies. The average number of employees is 430, with a median value of 94. 36% of companies do not conduct formal R&D and 28% of the company-year observations have at least one patent application.

In Table 2 we show descriptive statistics for the spillover weights. 99.6 percent of German companies with at least one patent application have at least one inventor based in Germany and 19.9 percent of those companies have at least one inventor based in the USA. Co-applications between German and US companies are less frequent. 43.2 percent of German companies with patent applications have at least one application together with another German company. The respective figure for co-applications with US-based companies is 3.6 percent.[8] 24.5 percent of German companies engage in research cooperations with a German partner. For US partners the respective figure is 4.8 percent. The most important cooperation partner both within Germany and based in the US is customers.

Table 3 contains correlations for the spillover weights. There is a positive correlation between having inventors based in the USA and having a cooperation partner in the USA, but it is not significant for the cooperation partners customer and supplier. This indicates that companies choose different channels for technology sourcing. The correlation between basing inventors abroad and cooperating abroad is lower than the correlations between the different cooperation types. The correlation between having inventors in Germany and having cooperation partners in Germany is higher than the respective US correlation, but the correlations between different cooperation partners are similar for the US and for Germany. The correlation of spillover weights for two activities in the same country tend to be higher than the corresponding correlation for one activity taking place between countries (e.g. in the US and in Germany).

4.2 Main Results

In Table 4 we present our regression results. The dependent variable is the log of sales. Column 1 shows the estimate of the basic production function. The estimates indicate constant returns to scale as the sum of the coefficients on the factor inputs (labor, material, capital and R&D) are very close to unity. The fixed-effects results for the production function are shown in column 2. The most prominent changes compared to OLS are a higher coefficient for labour input and a smaller coefficient for materials.

In column 3 we include industry level controls for R&D and value added in the US and Germany and the interaction term of industry-level R&D stock and share of inventors in the respective country. The coefficient on the interaction between US R&D and the proportion of a firm's inventors in the US is positive and highly significant. This is a key result – it is apparent that locating inventors in the USA helps to benefit from the knowledge available, just as the technology sourcing argument would claim. This result is consistent with the finding of Griffith et al. (2006) on UK data. The insignificance of the respective interaction term for Germany should not be interpreted as evidence that there are no knowledge spillovers within Germany. Companies based in Germany have by definition a local presence. There is no need for them to rely explicitly on local inventors in order to benefit from the local knowledge.[9]

Looking at the other results in column 3 it is clear that the industry-level value added in Germany has a positive correlation with productivity, which can be a reflection of higher capacity utilization due to positive demand shocks. The linear industry-level R&D stocks of Germany and the US have no direct influence on productivity.

In order to judge the economic significance of our results we calculate by how much German companies benefited from basing inventors in the USA. During the sample period of 1992-2003 the industry-level R&D stock in the USA increased by 21.4 percent. This increase is associated with a 14.7 percent increase in TFP for a German company with the average share of inventors based in the USA.[10] For comparison, Griffith et al. (2006) find a 5 percent increase in TFP for UK firms from basing inventors in the USA. The larger gain for the sample of German companies may be explained by differences in the sample composition. In the German sample we have many medium sized companies, whereas the UK sample is based on publicly listed firms. For the medium sized companies it is presumably a higher hurdle to base inventors in the US, so it makes sense that they would require higher benefits from this investment.

In Table 5 we investigate the effectiveness of different types of technology sourcing. We find that more intense collaboration resulting in patent co-applications has an additional beneficial influence on TFP (column 1). A higher intensity of interactions lets companies benefit more from local knowledge.

Columns 2-6 of Table 5 consider the interaction with different partners in R&D cooperations. Looking at all partners together, we do not find a significant influence (column 2). When looking separately at the different types of partner we do uncover some interesting heterogeneity. Cooperation with customers (column 3) does not increase technology sourcing. Cooperation with customers are often agreed upon in order to adapt existing products to new markets so the R&D stock of the host country may not be so important for this activity. It is more important to know what customers want and the required changes can possibly be implemented with the R&D that the German company has already undertaken at home.

By contrast we find that cooperation with suppliers increase technology sourcing from the US (column 4). This form of open innovation is beneficial because it allows developing more specialized inputs for the production process, which have a very good fit for the buying firm. Cooperation with competitors also increases productivity through technology sourcing from both the US and Germany (column 5). Firms get access to relevant knowledge and realize cost reductions through the avoidance of duplication of research. Note that the magnitude of the interaction term with inventor location remains largely stable when additional controls for cooperation are included. This suggests that both activities make independent contributions to knowledge sourcing.

In column 6 we include all technology sourcing mechanisms simultaneously. Filing co-applications and cooperating with suppliers are the most important interactions as they remain statistically significant. The interaction terms for cooperation with both US and German suppliers are significant. One reason for this may be that US suppliers could be closer to the technology frontier than German suppliers and so have a bigger impact on TFP. The results of Table 5 are more speculative than Table 4 because is it not possible to base the weights for cooperations on pre-sample information. [11]

We also investigate the relative importance of the sourcing variables in an ‘R-squared’ sense. Dropping the co-application variables reduces ‘R-squared within’ by 0.002. Dropping the supplier variables has only two thirds of the effect and dropping the customer or competitor variables hardly changes R-squared. We therefore conclude that co-applications and cooperation with suppliers are the most important mechanisms for international technology sourcing.

4.3 Some Robustness Checks

Table 6 includes a number of robustness checks. First, we were concerned with the possible endogeneity of the weights as they use information within the estimating period (1992-2003) even though they are time invariant. Consequently, for the calculation of the share of inventors based in the USA and in Germany we use pre-sample patent information, i.e. we only use the information from patent applications that have been filed before the first year in which the company enters our sample. Column 1 shows that our results are robust to this experiment.

In columns 2-4 of Table 6 we estimate the model on sub-samples of industries. We divide these into high, medium and low R&D to sales sectors. Following Grupp and Legler (2000) high R&D intensity sectors had more than 7% R&D to sales ratios, low R&D industries had under 2.5% of sales in R&D and medium sectors were the residual. Basing inventors in the US is an effective form of technology sourcing for companies in industries with high and medium R&D intensity (columns 2 and 3), but not for the low sectors (column 4). In columns 5 to 6 we restrict the sample to companies with at least one patent application. The results on the positive influence on TFP of basing inventors in the US or filing patent applications together with US-based companies are confirmed.

Table 7 contains further robustness checks for our baseline specification from column 6 of Table 5. In column 1 we include an additional interaction of industry R&D stocks with the size of the patent stock of the firms to control for a levels effect that comes through the number of patents. As the additional interactions are insignificant and the main interactions remain significant, we can conclude that our results do not simply reflect size related advantages in technology sourcing. In column 2 we include an additional interaction of industry R&D stocks with firm R&D as R&D might help firms absorb knowledge spillovers (the "second face" of R&D as in Griffith et al., 2004). Again we find that the additional interactions are insignificant. In our baseline results, the share of inventors based in the US is set to zero for firms without inventors in the US and for firms without any patents at all. To exclude the possibility that this modeling choice induces distortions we include in column 3 an interaction of industry R&D stocks with a dummy for no patents. As before, the additional interaction terms are insignificant, and our main results do not change. Lastly, column 4 contains a specification with industry-year fixed effects. Even though this is a demanding specification as it absorbs all the industry R&D terms, the US interaction terms remain significant.

Table A1 in the appendix includes robustness checks based on GMM estimators. Estimating the production function with GMM allows us to take the possible endogeneity of the input factors into account. The fixed effects results of column 3 from Table 4 are confirmed by the

GMM estimates of Table A1. This table presents several variants of the GMM estimator which show the robustness of our results.[12]

We have tried to keep the analysis as comparable as possible to Griffith et al. (2006) to aid comparison. What are the main differences between this paper and their earlier UK-US comparison? First, Griffith et al. (2006) used value added as an output whereas we use output and control for materials on the right hand side. This is because materials data is not consistently available for the firm-level UK data from Datastream that Griffith et al. (2006) used whereas it is available in our German data. Our output-based production function is more general than that in Griffith et al. (2006) and so so nests their specification. Second, Griffith et al. (2006) use USPTO data whereas we use EPO application data. German firms are much more likely to patent at the EPO than USPTO so it seems a more appropriate source to use to construct the weights. Moreover, EPO data does not have a lead inventor (so we use all inventors). Finally, we use all applicants, rather than just those which were subsequently granted which is what Griffith et al. (2006) use. This is because non-granted applicant data was unavailable from the USPTO prior to 2001. Third, Griffith et al. (2006) uses pre-sample information to construct the weights whereas we use all patent information (including in-sample information) to construct the weights. This is because USPTO data is available back to 1965 whereas the EPO data only goes back to 1978 when the EPO was founded. Furthermore, German firms made full use of the possibility to patent at the EPO only towards the end of the 1980s, which further restricts the informational content of the early years. Nevertheless as column 1 of Table 6 shows, the results are robust to just using pre-sample weights. Finally, the preferred results in Griffith et al. (2006) are on System GMM. We found that the additional "Blundell-Bond" moment restrictions were rejected in the German data and therefore present the Arellano-Bond results in Table A1.

5 Conclusions

This paper investigates technology sourcing activities of German companies in the USA. We find that being closer to the knowledge source has a positive influence on the TFP of the companies. German companies with inventors in the USA benefit from the US knowledge stock. We also find that differences in the type of R&D activity matter. It is important how close contacts are and closer contacts are better for technology sourcing. We find that co-patenting has an additional effect compared to simply locating inventors abroad. The type of cooperation partner matters as well. Companies cooperating with suppliers benefit from the local knowledge stock whereas cooperations with customers and competitors do not leave notable traces in our productivity measures.

For managers it is important to consider which type of R&D activity they conduct abroad. By basing inventors abroad the firms can profit from localized spillovers to which they would otherwise not have access. Our results also suggest that performing “open innovation” by cooperating with suppliers allows the firm to improve operations. Our results do not imply that cooperation with customers and competitors is not beneficial for firms. One should keep in mind that we only measure effects on the productivity of the firm in the home country. Cooperation with customers can be a boost to selling the products abroad, even if it does not increase the productivity at home. Influencing standards and the regulatory environment can be beneficial for the long-term development of the firm, even if it does not have a direct influence on productivity.

We conclude that it can be positive for the own country, if companies send researchers abroad, since it makes the own companies more productive. The potential loss of highly qualified jobs should not be the only consideration when R&D activities are internationalized.

A specific form of brain drain can be good. It may be especially worthwhile to encourage cooperation with foreign partners for advanced R&D activities.

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TABLE 1 –
DESCRIPTIVE STATISTICS – PRODUCTIVITY VARIABLES

Variable	Mean	Median	Stdev.	Min	Max
Sales	79.7	8.67	718	0.066	21,838
Employment	430	94	2,679	1	66,781
Materials	44.6	3.49	504	0.005	17,814
Capital	27.6	3.20	254	0.011	8,631
Firm R&D	14.6	0.236	173	0	5,405
Dummy zero firm R&D	0.360	0	0.480	0	1
Dummy Eastern Germany	0.325	0	0.468	0	1
R&D intensity (in %)	1.57	0.074	3.14	0	37.5

Note: Variables measured in million Euro, deflated to 1995 prices.

TABLE 2 –
DESCRIPTIVE STATISTICS – SPILLOVER WEIGHTS

	Interaction with the US		Interaction within GER	
Variable	Mean	Obs. > 0	Mean	Obs. > 0
Dummy Inventor	0.199	386	0.996	1933
Dummy Co-application	0.036	69	0.432	250
Cooperation any partner	0.048	309	0.245	1578
Cooperation customer	0.041	262	0.166	1069
Cooperation supplier	0.014	93	0.152	978
Cooperation competitor	0.013	87	0.084	541

Note: Dummy Inventor and Dummy Co-application for companies with at least one patent application. Dummy Inventor is equal to one if the company has at least one inventor in the respective country. Dummy Co-application is equal to one if the company has at least one Co-application with a company outside the own group in the respective country.

TABLE 3 –
CORRELATIONS SPILLOVER WEIGHTS

	% Inv. in US	% Coapp. in US	Coop. US customer	Coop. US supplier	Coop. US comp.	% Inv. in GER	% Coapp. in GER	Coop. GER customer	Coop. GER supplier	Coop. GER comp.
% Inventors in US	1									
% Co-applications in US	0.220*	1								
Coop. US customer	0.019	0.008	1							
Coop. US supplier	0.019	0.001	0.364*	1						
Coop. US competitor	0.255*	-0.007	0.480*	0.347*	1					
% Inventors in GER	0.125*	0.094*	0.265*	0.142*	0.156*	1				
% Co-applications in GER	0.010	-0.0001	0.119*	0.116*	0.034*	0.185*	1			
Coop. GER customer	0.043*	0.048*	0.392*	0.247*	0.212*	0.273*	0.114*	1		
Coop. GER supplier	0.029*	0.053*	0.272*	0.174*	0.119*	0.216*	0.071*	0.517*	1	
Coop. GER competitor	0.125*	0.156*	0.230*	0.128*	0.256*	0.184*	0.036*	0.355*	0.290*	1

Note: * indicates significance at the 5 percent level.

TABLE 4 –
R&D AUGMENTED PRODUCTION FUNCTIONS

	(1)	(2)	(3)
	OLS	FE	FE
Dependent variable	Ln(Sales)		
% Inventors in US* ln(US industry R&D)			0.690**
			(0.343)
% Inventors in GER* ln(GER industry R&D)			-0.015
			(0.019)
Ln(employment)	0.400***	0.515***	0.514***
	(0.015)	(0.022)	(0.022)
Ln(materials)	0.494***	0.272***	0.271***
	(0.011)	(0.018)	(0.018)
Ln(capital)	0.094***	0.079***	0.079***
	(0.008)	(0.013)	(0.013)
Ln(firm R&D)	0.027***	0.028***	0.026***
	(0.006)	(0.007)	(0.007)
Ln(US industry R&D)			-0.015
			(0.018)
Ln(GER industry R&D)			-0.001
			(0.018)
Ln(US industry value added)			0.005
			(0.020)
Ln(GER industry value added)			0.113**
			(0.047)
Observations	6447	6447	6447
R-squared / R-squared within	0.98	0.62	0.62
Number of firms	910	910	910

Note: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively. Standard errors are clustered by firm. All regressions contain year dummies and a dummy if R&D is zero. Column (1) includes a dummy for East Germany and two digit industry by year interactions.

TABLE 5 –
R&D AUGMENTED PRODUCTION FUNCTIONS – TYPE OF INTERACTION

Dependent variable	(1) Ln(sales)	(2)	(3)	(4)	(5)	(6)
% Inventors in US* ln(US industry R&D)	0.492** (0.233)	0.585 (0.367)	0.625* (0.365)	0.607* (0.345)	0.674** (0.343)	0.508** (0.263)
% Inventors in GER* ln(GER industry R&D)	-0.015 (0.018)	-0.027 (0.021)	-0.022 (0.021)	-0.032 (0.020)	-0.023 (0.020)	-0.028 (0.021)
% Coapp. in US* ln(US industry R&D)	11.02* (5.70)					10.92** (5.66)
% Coapp. in GER* ln(GER industry R&D)	0.005 (0.005)					0.005 (0.005)
Cooperation US any* ln(US industry R&D)		0.027 (0.051)				
Cooperation GER any* ln(GER industry R&D)		0.026 (0.021)				
Cooperation US customer* ln(US industry R&D)			0.016 (0.049)			-0.050 (0.050)
Cooperation GER customer* ln(GER industry R&D)			0.021 (0.023)			-0.018 (0.033)
Cooperation US supplier* ln(US industry R&D)				0.228** (0.103)		0.270** (0.110)
Cooperation GER supplier* ln(GER industry R&D)				0.038* (0.020)		0.056** (0.028)
Cooperation US comp.* ln(US industry R&D)					0.104** (0.051)	0.023 (0.066)
Cooperation GER comp.* ln(GER industry R&D)					-0.003 (0.040)	-0.018 (0.042)
Ln(employment)	0.516*** (0.022)	0.515*** (0.022)	0.514*** (0.022)	0.513*** (0.022)	0.513*** (0.022)	0.515*** (0.022)
Ln(materials)	0.269*** (0.017)	0.271*** (0.018)	0.271*** (0.018)	0.270*** (0.017)	0.271*** (0.018)	0.268*** (0.017)
Ln(capital)	0.078*** (0.013)	0.078*** (0.013)	0.078*** (0.013)	0.079*** (0.013)	0.079*** (0.013)	0.079*** (0.013)
Ln(firm R&D)	0.025*** (0.007)	0.026*** (0.007)	0.026*** (0.007)	0.026*** (0.007)	0.025*** (0.007)	0.026*** (0.007)
Ln(US industry R&D)	-0.015 (0.018)	-0.015 (0.018)	-0.016 (0.018)	-0.019 (0.018)	-0.017 (0.018)	-0.019 (0.019)
Ln(GER industry R&D)	0.001 (0.018)	-0.008 (0.019)	-0.004 (0.018)	-0.006 (0.018)	0.0004 (0.018)	-0.005 (0.019)
Ln(US industry value added)	0.008 (0.020)	0.003 (0.020)	0.004 (0.020)	0.001 (0.020)	0.004 (0.020)	0.005 (0.020)
Ln(GER industry value added)	0.113** (0.047)	0.111** (0.047)	0.112** (0.047)	0.113** (0.047)	0.114** (0.047)	0.115** (0.047)
Observations	6447	6447	6447	6447	6447	6447
R-squared within	0.62	0.62	0.62	0.62	0.62	0.62
Number of firms	910	910	910	910	910	910

Note: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively. Standard errors are clustered by firm. All regressions contain year dummies, fixed effects and a dummy if R&D is zero. The dependent variable is ln(sales). Estimation is by within groups including a dummy variable for each firm.

TABLE 6 – ROBUSTNESS

Experiment	(1) Pre sample weights	(2) High R&D industries	(3) Medium R&D industries	(4) Low R&D industries	(5) Firms with at least one patent	(6) Firms with at least one patent
% Inventors pre sample in US* ln(US industry R&D)	0.669** (0.327)					
% Inventors pre sample in GER* ln(GER industry R&D)	-0.045** (0.021)					
% Inventors in US* ln(US industry R&D)		0.736*** (0.165)	3.009** (1.233)	-0.089 (0.419)	0.807* (0.414)	0.572** (0.250)
% Inventors in GER* ln(GER industry R&D)		-0.060 (0.076)	0.018 (0.081)	0.007 (0.035)	0.020 (0.045)	0.0001 (0.038)
% Coapp. in US* ln(US industry R&D)						9.713* (5.275)
% Coapp. in GER* ln(GER industry R&D)						0.002 (0.004)
Ln(employment)	0.514*** (0.022)	0.530*** (0.073)	0.463*** (0.039)	0.529*** (0.027)	0.561*** (0.041)	0.568*** (0.040)
Ln(materials)	0.272*** (0.018)	0.255*** (0.040)	0.334*** (0.035)	0.254*** (0.021)	0.324*** (0.039)	0.318*** (0.039)
Ln(capital)	0.078*** (0.013)	0.126*** (0.031)	0.065** (0.025)	0.072*** (0.016)	0.059** (0.025)	0.059** (0.026)
Ln(firm R&D)	0.026*** (0.007)	0.002 (0.020)	0.025 (0.018)	0.026*** (0.008)	0.034*** (0.013)	0.034** (0.013)
Ln(US industry R&D)	-0.013 (0.018)	-0.351*** (0.101)	-0.052 (0.057)	0.012 (0.027)	-0.0005 (0.028)	-0.005 (0.027)
Ln(GER industry R&D)	0.004 (0.018)	0.021 (0.060)	0.011 (0.062)	-0.015 (0.021)	-0.055 (0.053)	-0.030 (0.044)
Ln(US industry value added)	0.004 (0.020)	0.106 (0.078)	-0.032 (0.035)	-0.007 (0.045)	0.014 (0.029)	0.023 (0.028)
Ln(GER industry value added)	0.118** (0.047)	0.051 (0.093)	0.139 (0.141)	0.106* (0.060)	-0.038 (0.067)	-0.031 (0.066)
Observations	6447	562	1531	4354	1941	1941
R-squared within	0.62	0.73	0.63	0.60	0.71	0.71
Number of firms	910	83	247	631	287	287

Note: *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors clustered by firm. All regressions contain fixed effects, year dummies and a dummy if R&D is zero. The dependent variable is ln(sales).

TABLE 7 –

ROBUSTNESS – ADDITIONAL CONTROLS

Dependent variable	(1) Ln(sales)	(2)	(3)	(4)
% Inventors in US* ln(US industry R&D)	0.426*	0.543**	0.586**	0.748***
	(0.252)	(0.256)	(0.267)	(0.249)
% Inventors in GER* ln(GER industry R&D)	-0.031	-0.027	-0.003	-0.016
	(0.023)	(0.021)	(0.042)	(0.025)
% Coapp. in US* ln(US industry R&D)	10.149*	10.983*	10.745*	11.234*
	(5.447)	(5.664)	(5.645)	(5.940)
% Coapp. in GER* ln(GER industry R&D)	-0.002	0.005	0.005	0.004
	(0.006)	(0.005)	(0.005)	(0.004)
Cooperation US customer* ln(US industry R&D)	-0.049	-0.042	-0.054	-0.032
	(0.050)	(0.050)	(0.051)	(0.055)
Cooperation GER customer* ln(GER industry R&D)	-0.010	-0.017	-0.018	-0.002
	(0.033)	(0.033)	(0.033)	(0.036)
Cooperation US supplier* ln(US industry R&D)	0.269**	0.280**	0.268**	0.360***
	(0.112)	(0.109)	(0.111)	(0.112)
Cooperation GER supplier* ln(GER industry R&D)	0.050*	0.061**	0.055**	0.099***
	(0.028)	(0.028)	(0.028)	(0.035)
Cooperation US comp.* ln(US industry R&D)	0.016	0.016	0.024	-0.023
	(0.067)	(0.066)	(0.066)	(0.075)
Cooperation GER comp.* ln(GER industry R&D)	-0.020	-0.022	-0.018	-0.068
	(0.042)	(0.042)	(0.042)	(0.052)
ln(firm patent stock) * ln(US industry R&D)	0.001			
	(0.002)			
ln(firm patent stock) * ln(GER industry R&D)	-0.000			
	(0.002)			
Ln(firm R&D) * ln(US industry R&D)		-0.002		
		(0.002)		
Ln(firm R&D) * ln(GER industry R&D)		0.000		
		(0.001)		
Dummy no patents* ln(US industry R&D)			-0.007	
			(0.037)	
Dummy no patents* ln(GER industry R&D)			0.030	
			(0.052)	
Ln(employment)	0.514***	0.515***	0.515***	0.511***
	(0.022)	(0.022)	(0.022)	(0.021)
Ln(materials)	0.268***	0.268***	0.268***	0.267***
	(0.017)	(0.017)	(0.017)	(0.016)
Ln(capital)	0.077***	0.079***	0.079***	0.071***
	(0.013)	(0.013)	(0.013)	(0.013)
Ln(firm R&D)	0.024***	0.041***	0.026***	0.025***
	(0.007)	(0.013)	(0.007)	(0.007)
Ln(US industry R&D)	-0.011	-0.027	-0.020	
	(0.022)	(0.020)	(0.022)	
Ln(GER industry R&D)	-0.007	-0.004	-0.003	
	(0.024)	(0.020)	(0.021)	
Ln(US industry value added)	0.003	0.006	0.004	
	(0.020)	(0.020)	(0.020)	
Ln(GER industry value added)	0.110**	0.123***	0.115**	
	(0.047)	(0.047)	(0.047)	
Observations	6,447	6,447	6,447	6,447
R-squared within	0.623	0.623	0.623	0.647
Number of firms	910	910	910	910

Note: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively. Standard errors are clustered by firm. All regressions contain year dummies, fixed effects and a dummy if R&D is zero. Column 4 contains industry-year fixed effects. The dependent variable is ln(sales).

APPENDIX TABLES

TABLE A1 –
ARELLANO-BOND GMM SPECIFICATIONS

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Ln(sales)				
Specification	Baseline	Use t-3 moments	Treat R&D as strictly exogenous	Static	Add sales as an IV
% Inventors in US* ln(US industry R&D)	0.847***	0.882***	0.709***	0.471**	1.175**
	(0.283)	(0.310)	(0.269)	(0.213)	(0.572)
% Inventors in GER* ln(GER industry R&D)	-0.040	-0.038	-0.043	-0.019	-0.047
	(0.027)	(0.027)	(0.027)	(0.022)	(0.042)
Ln(US industry R&D)	-0.025	-0.025	-0.023	-0.005	-0.039
	(0.018)	(0.018)	(0.019)	(0.022)	(0.024)
Ln(GER industry R&D)	-0.007	-0.004	-0.007	-0.022	0.0004
	(0.020)	(0.020)	(0.022)	(0.023)	(0.024)
Ln(US industry value added)	0.031	0.027	0.035	0.038	-0.040
	(0.024)	(0.027)	(0.027)	(0.027)	(0.034)
Ln(GER industry value added)	0.062	0.082	0.073	0.058	0.028
	(0.067)	(0.068)	(0.072)	(0.057)	(0.078)
Observations	4627	4627	4627	5537	4627

Note: *, **, *** indicate statistical significance at the 10, 5, and 1 percent levels, respectively. Standard errors clustered by firm. All regressions are based on the specification in column (5) of table 4. We include current and lagged values of firm sales, capital, labour, materials, firm R&D, a dummy if R&D is zero or missing and year dummies. The dependent variable is ln sales. We use the Arellano-Bond (1991) moments treating all firm level variables as endogenous. One-step estimates reported. Note that the additional moments suggested by Blundell and Bond (1998) were found to be rejected, so we do not use them. Column (1) repeats the baseline. Column (2) only uses instruments dates t-3 or earlier in order to allow for the possibility of first-order serial correlation (in the levels error). Column (3) treats R&D as strictly exogenous instead of endogenous. Column (4) drops the lagged values of firm-level variables (keeping the IV set the same). Column (5) includes sales t-2 and prior in the IV set.

Endnotes

[1] For surveys of this development see Keller (2004), Narula and Zanfei (2005) and Cantwell (2009).

[2] See Audretsch and Feldman (1996) and Jaffe et al. (1993) on local restrictions of spillovers. Geographic boundaries to knowledge spillovers are also considered in Jaffe and Trajtenberg (1999), Branstetter (2001), Keller (2002) and Almeida and Kogut (1999).

[3] For evidence on technology sourcing through FDI see Smarzynska (2004). For evidence on importance of outward FDI as indicator of technology sourcing see van Pottelsberghe de la Potterie and Lichtenberg (2001). Naturally, knowledge flows may be bi-directional (Singh, 2007).

[4] Turnover is deflated by two digit industry prices, material costs is deflated by the GDP deflator, capital stock is deflated by the producer price index for capital equipment, and R&D is deflated by a weighted average of the wage development in manufacturing (50%), the GDP deflator (40%) and the producer price index for capital equipment (10%):

[5] If there is no tangible stock in the first year we use the investment flow and scale it up based on the assumed steady state growth (5%) and depreciation rate (15%). If there is no investment flow in subsequent years to the initial year we use the tangible capital stock.

[6] For the interaction terms we use the patent portfolio of the whole group if the sample company is a subsidiary. This implies that we cover the knowledge that can be accessed from within the group. Looking only at the patent portfolio of the subsidiary would miss important parts of the access to knowledge.

[7] The MIP data also provides information on cooperation with research institutions in the USA. We do not include this cooperation category because the number of companies with such a type of cooperation is too limited (there are only 8 firms).

[8] Note that in the regressions we use the share of inventors based in Germany or in the USA and not a dummy whether the company has at least one inventor based in Germany or in the USA. The same applies to the variable for coapplications.

[9] We also tested whether German companies benefit from basing inventors in Japan. We obtain a positive, but insignificant coefficient on the interaction term. The insignificance can be due to fewer observations with inventors in Japan or to lower gains from technology sourcing. Our sample has not enough observations for research cooperations with Japanese partners to allow for meaningful results.

[10] The increase in the US R&D stock of 21.4 percent is multiplied by 0.690, which is the coefficient on the variable "%Inventors in US * ln(US industry R&D)". The calculation is based on the specification shown in Table 4, column 3.

[11] Following Blundell and Bond (1998, 2000) we test for weak instruments by regressing the first difference of the endogenous variables on the t-2 lagged levels of the instruments, i.e. we calculated the first-stage for the instruments with Anderson-Hsiao style instruments. For all of the 11 first stages of our main specification we could confirm the joint significance of the instruments at least at the 1% level.

[12] When using GMM for the specification of Table 5, column 6 instead of a fixed-effects approach, we obtain qualitatively similar results for placing inventors in the US and for cooperating with US-based partners. For jointly filing patents with US co-applicants we find insignificant coefficients.

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