ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Working Paper Series

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December 2018

Institute for Technology and Public Policy
Working Paper series no. 5

Available at: https://ideas.repec.org/p/iip/wpaper/5.html

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Abstract

Offshoring R&D commonly invokes concerns regarding the loss of high value jobs and a hollowing out of technological capabilities, but it can also benefit domestic firms by enabling them to tap into the global technological frontier. We study the effect of R&D offshoring on industrial productivity in the home country using industry-level data for 18 OECD countries over a 26-year period. Simultaneity between productivity and R&D offshoring is addressed by using foreign tax policy as an instrument for offshored R&D. We show that R&D offshoring contributes positively to productivity in the home country, irrespective of the host country destination.

JEL classifications: F23, F62, O25, O33, O47, L6

*Keywords***:** R&D offshoring, globalization, productivity, foreign R&D

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Introduction

This article investigates the impact of research and development (R&D) offshoring on industrial productivity in the home country and considers factors that may condition the effect. Globalised technology sourcing is a defining feature of innovation systems in the 21st century. By 2008, US-owned manufacturing companies performed nearly 20 percent of their total R&D outside the United States (NSF 2010). The extent of R&D offshoring by several European countries including Switzerland, Sweden and Germany appears to be even greater (European Commission 2012). The growth in R&D offshoring has long been regarded as a worrisome development for technologically advanced nations in light of the central role of R&D in driving productivity and economic growth (Mansfield *et al*. 1979; Lall 1979; Dunning 1994). Governments are increasingly inclined to offer inducements in order to ensure that 'national' firms maintain R&D activities in their historical home country.

Recent evidence has shown that firms can generate private benefits from offshoring R&D. By tapping into the globally disparate technological frontier firms can enhance their productivity and market position (Cantwell 1995). For instance, Samsung's R&D outpost in Silicon Valley is credited with playing a vital role in the company's eventual dominance in SDRAM technologies (Kim 1997). Analyses of data on firms based in the UK and Germany have shown that offshoring R&D to the United States provides a means to benefit from technological spillovers and enhance performance (Griffith *et al.* 2006; Harhoff *et al.* 2012).

Notwithstanding the evidence regarding benefits to the offshoring firms themselves, the overall impact on the home country is not yet clear. The important role of Samsung in Korean economic development suggests that impacts can potentially be substantial, but to what extent is this example an exception rather than a rule? Of concern is the loss of 'scientist-to-scientist' spillovers, which are thought to occur at the location in which R&D is performed. Equally importantly, benefits associated with offshored R&D are expected to be dispersed across the company's global operations; there is no guarantee that a substantive share will be captured by operations in the home country. Additionally, benefits may be muted in the case of home countries at the technological frontier because the relative technological capacity of the home country determines scope for learning (Song and Shin 2008; Song *et al.* 2011). Using data on international investments projects for R&D, Castellani and Pieri (2013) document a positive association between R&D offshoring and home region productivity growth. The extent to which benefits may hinge on offshoring to an advanced economy has not been subject to direct empirical scrutiny though Griffith *et al.* (2006) note in passing that they are unable to confirm a positive impact from offshoring to countries other than to the United States. This finding is cause for concern to policy makers in the United States, which is the home country to firms engaged the most in R&D offshoring.

We study the effect of R&D offshoring on industrial productivity in the home country using new patent-based indicators of R&D offshoring linked to 2-digit manufacturing production data from 18 OECD countries between 1981 and 2007. Our industry-level approach provides a global and long-term view and avoids many of the sampling and selection issues inherent in firm level studies. It captures the net effect on local industry taking into account spillover effects, which are an important component of the policy puzzle. After all, we expect firms to derive private benefit from their own offshoring decisions, at least on average.

We also extend the literature by tackling the difficult issue of simultaneity between productivity and offshoring—an issue that existing literature has neglected. Simultaneity arises because home country technological capacity determines the existence of leading multinational enterprises (MNEs) as well as their capacity to manage and benefit from globally dispersed R&D assets (Vernon 1966; Patel and Pavitt 1988, 1991; Le Bas and Sierra 2002; Song and Shin 2008; Song *et al.* 2011). To address the issue of simultaneity we use country-industry specific measures of R&D tax policy as an instrument for R&D offshoring activity. R&D tax policy provides a promising instrument since foreign tax policy is exogenous to domestic productivity—it is difficult to imagine a mechanism through which R&D specific tax incentives in the UK will affect industrial productivity in the United States except via their influence on the distribution of company R&D between the two countries. Besides, R&D tax incentives have been shown to have a significant influence on R&D location decisions (Bloom and Griffith 2001; Wilson 2009). We also consider a conventional application of systems GMM (Blundell and Bond 1998).

Our results show that R&D offshoring contributes positively to productivity in the home country, irrespective of the host country destination. However, we report evidence suggesting that the benefits hinge on the nature of offshoring activities, with technology-seeking offshored R&D bringing the most benefits and market-seeking offshored R&D potentially harming productivity.

Theoretical framework

In light of the ongoing growth in R&D offshoring it would be difficult to argue that firms are not generating private benefits from their offshored R&D activities. Scholars have long recognized that offshoring provides a critical mechanism to tap into the globally disparate technological frontier (Ronstadt 1978; Cantwell 1995). Offshoring provides a means for firms to procure technologies not necessarily available in the home market. All the 25 most patent-intensive U.S. companies perform some R&D abroad—and every one of them acquires patents from abroad in technology areas that they do not acquire from local R&D (own analysis, derived from USPTO data).

Our research question deals with not just the magnitude of benefits of R&D offshoring but also the distribution of those benefits. Benefits from R&D activity accrue to the investing firm and can also spill over to neighboring firms. In this section we begin by considering each of these in turn, with a view to articulating the mechanism through which R&D offshoring impacts productivity in the home country. We then discuss factors that may mitigate or condition the effect.

Some of the value generated by new technology will be captured by the plant where the technology is implemented; this may be the country in which the research was conducted, in the firm's home-base, or in a third country in which the firm has production assets. Value is also captured at other points along the firm's value chain. The share of value captured by manufacturing activities *per se* in global value chains is typically low and appears to be falling (Bartlett and Ghoshal 2000; Ali-Yrkkö and Rouvinen 2015). Value also permeates upstream and downstream global value chains, with a large share of value added captured by operations in the home country, including headquarter operations as well as niche high-value contributions to production activities (Ali-Yrkkö and Rouvinen 2015).

It is well understood that firms generally do not capture all benefits associated with R&D investment. Benefits also spill over to neighboring firms and these spillovers also contribute to the geographic distribution of benefits of offshored R&D. Spillovers can arise at three loci of the innovation process: invention, production and ownership. Those at the invention stage are well understood and involve the formal and informal exchange of information between scientists. Although the literature emphasises that knowledge spillovers are highly localised (Jaffe *et al.* 1993), spillovers from offshored R&D to other firms in the home country have also been documented (Criscuolo 2009). Spillovers associated with the production processes where technologies are implemented are similarly well understood. Like internalised benefits, they are diffused along the production chain and work through interactions with suppliers, demonstration effects and engineering and management consultancy. Firms in the home country can benefit from the offshoring activities of their compatriots via demonstration effects or through supply-chain-mediated technology upgrading (Porter 1990). Trade in intermediate goods is also an important transmission mechanism for productivity gains at the production stage (Griliches 1979). Finally, technology owners in the home country hold managerial and strategic insights that can benefit local upstream and downstream actors.

Not all R&D offshoring is expected to bring equal benefits to the home country. For instance, R&D offshoring that is intended primarily to adapt products for specific local markets (known as 'market-seeking' R&D) is unlikely to generate extensive spillovers to the firm's home country (*cf.* Arvanitis and Hollenstein 2011). Scope for learning can also influence firm level benefits (Song and Shin 2008; Song *et al.* 2011). Recent research has emphasised the importance of offshoring R&D to technological leaders and the United States in particular (Griffith *et al.* 2006; Criscuolo 2009; Harhoff *et al.* 2014). Although the United States is certainly a leader by many aggregate measures, the existence of centers of excellence around specific technology areas and niche technical and scientific skills in other parts of the world scarcely requires argument. Global technology strategy provides a mechanism for sourcing the best technology from an increasingly globally disparate frontier. If informed firms act rationally in choosing the location of offshored R&D we should expect all offshored R&D investments to generate returns commensurate with the risks and costs they involve.

Simultaneity between offshoring and performance has, to date, largely escaped the modeling effort of empirical economists (Griffith *et al.* 2006:1873). Micro-level evidence suggests that leading MNEs have most to gain from R&D offshoring because of their superior absorptive capacity (Song and Shin 2008). Leading firms also possess organization capabilities that allow them to manage the complex process of R&D offshoring, so that they are the most likely to engage in that activity. Insights from management studies similarly suggest that R&D offshoring is the privilege of the fittest (Patel and Vega 1999; Le Bas and Sierra 2002). Concern about the endogeneity of the R&D offshoring decision is somewhat less salient at the industry level than at the firm level. However, because we cannot rule out the possibility that offshoring is endogenous to performance, we implement an instrumental variable approach, as explained further below.

Measuring home and offshored R&D

Ideally, we would observe industry level R&D expenditures by country of funding (the firms home base) and country of performance (the host country). Unfortunately, statistical agencies do not collect such data systematically. We resort to patent data, which provide an indicator of both home and offshored R&D (Guellec and van Pottelsberghe 2001; OECD 2009; Picci 2010; Thomson 2013).[1] Home R&D is captured with patents that have both domestic applicants and inventors. A patent application that derives from offshored R&D has a domestic applicant and a foreign inventor. The applicant's address provides an indicator of the MNE's home country and inventor's country of residence indicates the MNEs offshoring location.

In most cases, owners of valuable technology want protection from would-be imitators in many countries. To achieve this, they must file patent applications to the intellectual property office in each country they want protection. Patents are generally filed in production centers, major markets, and the location of competitor firms. The first filing protecting an invention is called a priority patent application. Subsequent applications protecting the same invention in

[1] A direct implication of using patent data is that our R&D measure focuses on technological innovations for which patent applications are sought. The well-known limitations of using patent data apply (*e.g.*, Griliches 1990). In practice, this choice means that we will miss cases where, say, a Swiss pharmaceutical firm outsources the clinical trials of a drug to an arm's length contract research organization in India.

other jurisdictions are called second filings. Only priority patent applications are included in our measure since second filings are not indicative of additional R&D activity.

The measure of offshoring is calculated using the universe of inventor-applicant pairs (including 'inventor countries' that are not in the OECD). Multi-inventor or multi-applicant patent applications that span more than one country are fractionally counted. The data come from the European Patent Office (EPO) Worldwide Patent Statistical Database PATSTAT (de Rassenfosse *et al.* 2014). The algorithm used to identify priority filings and to fill in missing data on applicant and inventor country of residence is discussed in de Rassenfosse *et al.* (2013). Figure 1 shows that the worldwide proportion of 'offshored patents' has grown, from 3 percent in the early 1980s to more than 10 percent in the late 2000s.

[Figure 1 about here]

We allocate patent applications across industrial sectors using the International Patent Classification (IPC)–industry concordance table developed by Schmoch *et al.* (2003).[2] The concordance table is derived from a complete enumeration of the patenting activity in technology-based fields of more than 3,000 firms that are classified by ISIC industrial sector. Some measurement error is inevitable in such concordance procedure, though we expect this measurement error to be largely stable over time meaning that it can be accommodated in the econometric model in the same manner as other time invariant heterogeneity.

Our patent data are unique because they provide a systematic, comprehensive and global view, though naturally, they capture the phenomenon of interest with some noise. We

[2] The IPC is a hierarchical patent classification system used in over 100 countries to classify the content of patents in the technology area to which they pertain.

take a number of steps to increase confidence that our patent-based indicators are representative of R&D activities. We discuss key aspects next.

Market-seeking R&D offshoring is anticipated to generate fewer benefits to the firms' home country. Our analysis focuses on technology-seeking R&D, which is identified by those patent applications that are *filed* in the home country (either as a priority filing or a second filing).[3] We argue that one can use filing behavior to identify technology- versus market-seeking R&D offshoring. Technology-seeking R&D is targeted at developing novel technologies that will be used in the company's global operations such that there are strong incentives to seek protection in the home country. By contrast, market-seeking offshored R&D is directed towards producing a technology for, or adapting it to, the local market. Since technology generated via market-seeking R&D offshoring has relatively market-specific usefulness there is limited impetus for the inventing firm to file for patent protection in the home country. Our approach of using filing behavior to measure the type of foreign R&D departs from previous work that uses citation data (*e.g.*, Frost 2001). Appendix A1 provides a lengthy comparison between our approach and a citation-based approach.

By focusing on patent applications that are *filed* in the home (applicant) country we also largely avoid measurement error associated with 'IP migration', which occurs when the applicant address is chosen purely for tax minimization purposes. There is no incentive for firms to file for patent protection in the Cayman Islands even if they allocate ownership to their Cayman Island subsidiary for the purpose of tax minimization.[4] Our sample avoids many of the policies that generate high-powered incentives to undertake IP migration. Well-known tax

[3] In the case of patent applications filed at the EPO, the patent application is assumed to be filed at home if the applicant resides in a member state of the European Patent Convention.

[4] Indeed, allocation/transfer of ownership for tax purposes mainly takes the form of intra-company transfers that need not be reported to the patent office in order to be effective.

havens such as the Cayman Islands are not included in our sample and the period of analysis pre-dates the 'patent box' policies implemented in the Netherlands, Belgium, Luxembourg, and Spain after 2007. A patent box is a special tax regime for revenues derived from IP that may incentivize firms to relocate their patents (Ciaramella 2017). Furthermore, for the countries in our sample, aggregate patterns of patent assignment are not consistent with what would be predicted by tax minimization. For example, in low-taxing Ireland more patents invented by residents of Ireland are assigned to foreign firms than foreign invented patents are assigned to Irish affiliates—precisely the opposite of what tax minimizing behavior would predict. While we see no strong *a priori* reason to suspect that any measurement error arising out of IP migration (should it exist) should be systematically related to changes in productivity at the industry level, we consider augmented empirical specifications in an effort to directly control for corporate income tax rate in the home country as part of our robustness checking.

[Table 1 – about here]

Table 1 shows that there were four million priority patent applications filed worldwide in the period between 1980 to 2007, among which 182 thousand (4 per cent) are the result of R&D offshoring. Restricting the count to patent applications filed in at least two jurisdictions (thus filtering out a large number of low-value patents) leads to a worldwide count of 1.6 million patent applications, of which approximately 8 per cent result from R&D offshoring.

We do not observe the ownership structure of patent applicants. As a consequence, patents that are invented and assigned to the same foreign subsidiary will not be included in the measure.[5] These comprise a minority share of total group filings; based on detailed analysis of

[5] For instance, patent application EP1288659A3 filed by the U.S.-based company Bayer Corporation and created by two U.S.-based inventors will not appear as an offshore patent application. Yet, Bayer Corporation is a subsidiary of the German company Bayer AG and should, in a logic, be recorded as resulting from offshored R&D. By contrast,

172 MNEs, Belderbos *et al.* (2009) report that 82% of patents belonging to MNE group are filed through the headquarters. The benefits of our large-scale empirical approach in terms of time and geographic coverages come at a cost of potentially underestimating the extent of R&D offshoring. We judge this cost to be minor in light of the fact that the extent of this measurement error is relatively small and there is no *a priori* reason that this will be related to the outcome variable. In any case, by controlling for time invariant heterogeneity and with our IV approach, we can have reasonable confidence that this measurement error does not affect the veracity of the results.

Supporting this assessment, we find that our patent-based measure is strongly correlated with other available measures of R&D offshoring. We validate our measure of offshored R&D by considering the relationship between patents assigned to foreign entities and the international flows of finance for the purposes of R&D. Data on bilateral R&D flows do not exist, however total R&D financed from abroad aggregated across partner countries are collected by national statistics agencies by way of firm level survey (effectively aggregate R&D 'onshoring'). The criteria for recording R&D by source of funds in the Frascati manual stipulates that "there must be a direct transfer of resources [and] the transfer must be both intended and used for the performance of R&D" (OECD 2002:114). It does not include foreign sourced loans or other general capital raising or general transfers from the parent firm. It also does not include R&D performed by MNE affiliates and financed through retained earnings.

Table 2 provides econometric evidence on the relationship. The dependent variable is the lagged amount of R&D financed from abroad (in million 2005 US PPPs) at the country level in panel A and at the country-industry level in panel B. Pooled cross-section and fixed effect

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patent application US20110083984A1 filed by the German company Bayer AG and created by seven U.S.-based inventors (and one Germany-based inventor) will count as resulting from R&D offshoring.

estimates suggest a strong relationship between the patent indicator and the relevant R&D flows, even when adding additional lags to the specification. The results show that the production of patents with foreign applicant is strongly determined by foreign financed R&D. They provide further confidence in the validity of our patent-based measure of offshored R&D.

[Table 2 – about here]

Statistical approach

We study the productivity effect of R&D offshoring using a standard Cobb-Douglas production function with labor (denoted by L), fixed capital (denoted by K) and technology (denoted by A^*).

$$Y = K^{\alpha} L^{1-\alpha} (A^*)^{\gamma} \tag{1}$$

We treat the distinction between technology from the home country and from abroad in an analogous manner to the treatment of basic and applied R&D proposed by Griliches (1986), allowing for the possibility that technology stock derived from offshored R&D (denoted by A_F) attracts a premium (or discount) δ relative to technology stock derived from home R&D (which is denoted by A_H).[6] That is:

$$A^* = A_H + (1+\delta)A_F = A(1+\delta S) \tag{2}$$

where $S = \frac{A_F}{A}$ is the share of technology stock generated via offshoring of the total $A = A_H + A_F$.

[6] Note that treating foreign R&D as a distinct complementary input (as in $Y = K^{\alpha} L^{1-\alpha} A_H^{\gamma} A_F^{\gamma'}$) implausibly implies that industries that undertake no offshoring can generate no output.

Transforming equation (1) gives the canonical form of our estimating equation:[7]

$$\ln\left(\frac{Y}{L}\right) \cong \alpha \ln\left(\frac{K}{L}\right) + \gamma \ln A + \gamma\delta \frac{A_F}{A} \tag{3}$$

To incorporate the dynamic evolution of productivity, we augment equation (3) with a lagged dependent variable giving a baseline estimation equation as:

$$\ln\left(\frac{Y}{L}\right)_{ijt} = \beta \ln\left(\frac{Y}{L}\right)_{ijt-1} + \alpha \ln\left(\frac{K}{L}\right)_{ijt} + \gamma \ln A_{ijt} + \gamma\delta \left(\frac{A_F}{A}\right)_{ijt} + \lambda_t + \mu_{ij} + \varepsilon_{ijt} \tag{4}$$

where the index i denotes the country, j the industry and t the year. The error structure is assumed to comprise country-industry fixed effects as well as year effects.

We model output of manufacturing sectors at the 2-digit level of the International Standard Industrial Classification (ISIC Revision 3, codes 15-36) in 18 countries over the period from 1980 to 2007. Data on value added, capital stock and employment are compiled from the OECD Structural Analysis Database (OECD 2011). Royalties are included in industry value added regardless of whether technology users in the home country or abroad pay the royalties.[8] Table 3 reports summary statistics for measures used in the regression analysis.

[Table 3 – about here]

The industry level approach suits well our purpose of providing a global and long-term view. In addition, it avoids selection issues, endemic in firm-level studies, arising out of the role of productivity in entry and exit decisions (see, *e.g.*, Olley and Pakes 1996; Breunig and Wong

[7] We considered an alternative approach based on first estimating a growth equation to derive an estimate of industry level total factor productivity, which is then modelled in an analogous manner. The results were quantitatively similar. We thank Jacques Mairesse for this suggestion.

[8] In the standard national accounts framework, royalties are counted as sales if the buyer is at home or as a service export if the buyer is foreign.

2008). However, there still remains the possibility that input choices are endogenous to productivity shocks, and the related concern regarding the persistence of productivity variables over time. Dynamic panel bias that arises due to correlation between the lagged dependent variable is also of concern (Nickell 1981). To address dynamic panel bias we estimate equation (3) using systems GMM (Blundell and Bond 1998). The GMM estimates reported use the asymptotically efficient two-step procedure and apply Windmeijer's (2005) correction to the standard errors.

As already discussed, accounting for potential simultaneity between productivity and R&D offshoring is fundamental to any attribution of causality.[9] We consider a number of approaches to addressing this issue. First, we implement an instrumental variable approach using a measure of the tax treatment of R&D in the home country and in potential offshore R&D host countries. Second, we also consider a more conventional route to disentangle the causal impacts using systems GMM by instrumenting offshored share of technology stock in a manner analogous to the autoregressive term. We elaborate the instrumental variable approach below.

The appropriateness and validity of tax policy as an instrument is well supported. The *a priori* case that foreign tax policy is exogenous to domestic productivity is sound. It is difficult to imagine a mechanism through which R&D specific tax incentives in the UK will affect industrial productivity in the United States except via their influence on the distribution of company R&D between the two countries. Evidence suggests that R&D tax policy influences firms' R&D location decisions (Hines 1993; Bloom and Griffith 2001; Wilson 2009). We expect tax policy to influence primarily the intensive margin (rather than extensive) for technology-seeking type R&D

[9] The instrumental variable approach also accounts for omitted variable bias. This supports our parsimonious model laid out in equation (4), which does not include several factors known to influence productivity such as human capital.

offshoring; we argue that the margin that is amenable to the influence of fiscal incentives is of greatest interest to policy.

Data used to measure R&D tax policy are adapted from Thomson (2017). The measure is based on the standard adaptation of Jorgenson's (1963) 'user cost of capital' first proposed by McFetridge and Warda (1983) and subsequently developed by Bloom *et al.* (2002), Wilson (2009) and others. The measure, referred to as the 'tax-price of R&D', reflects the breakeven benefit-cost ratio for a representative firms' marginal R&D investment to be profitable after tax, taking into account any reductions to corporate tax liabilities associated with each dollar invested in R&D. Our country-industry specific policy measure incorporates cross-country variation in tax treatment of different R&D expenditure types (*e.g.*, labor and capital) as well as inter-industry variation in mix of expenditures by type.

We first calculate the separate tax-price for each expenditure category for each country. The general formula for the tax price of R&D is given by:

$$\text{taxprice} = \frac{\text{ATC}}{1 - \text{CIT}} \tag{5}$$

where ATC is the after-tax cost of R&D allowing for reductions in corporate income tax liabilities that result from the expenditure; and CIT is the corporate income tax rate. The after-tax cost of R&D investment can be expressed in general terms as:

$$\text{ATC} = 1 - (\text{CIT}) \times \overbrace{(\text{NPV of allowable claims}) \times (\text{proportion deductable})}^{\text{Total value of allowable deduction}} - (\text{credit}) \tag{6}$$

Equation (6) states that a firm's after-tax cost is reduced by allowable deductions multiplied by the corporate income tax rate (CIT) as well as any tax credits. The value of deductions is determined by two factors: the net present value (NPV) of the stream of allowable claims; and the proportion of the NPV that can be deducted. In some countries eligible expenditure can be deducted at a rate greater than 100 percent.

The after-tax cost for of three categories of R&D expenditure were calculated: 'capital', 'labor' and 'other current'. Tax treatment of different types of expenditure varies in part because credits do not generally apply to all expenditure categories. For example, since 1994 Netherlands has provided a tax credit solely on R&D labour expenses. Tax treatment also varies because rates of allowable depreciation vary by category. The calculations include representative allowable deduction as well as eligibility to special credits or augmented deductions for each expenditure category. The NPV of deductions for relevant capital expenditures are based on allowable depreciation schedules that are defined in the national tax code. See Thomson (2017) for details.

To measure the effective tax price of offshored R&D for each country we use the average tax price across potential offshoring locations (*i.e.*, all other countries in the sample). Tax policy data are only available for OECD member states so non-OECD countries are not included in this calculation. This limitation has negligible impact on the measured weighted average offshored tax price as only a small fraction of patents are attributed to inventors who are residents of countries for which we do not have tax price information (see also Kumar 2001; Thomson 2013).

Does offshoring affect home country productivity?

Tables 4 and 5 provide the main regression results. Table 4 presents OLS and IV estimates and Table 5 presents GMM estimates.

Column (1) of Table 4 presents a baseline OLS estimate without dynamic adjustment (corresponding to equation 3) and column (2) includes the dynamic adjustment term (lagged value of output per worker). Column (3) reports results of the fixed effect estimator and directly correspond to the specification in equation (4). These estimates may suffer from the endogeneity of input choices and the R&D offshoring decision, and dynamic panel bias. Thus, the parameter estimate should be treated with some caution. All we need to emphasize at this stage is that the coefficient associated with the R&D offshoring variable is positive and statistically significant.

Column (4) and (5) show the instrumental variable model. Column (4) shows the results of the first stage regression, which models the instrumented variable (share of technology stock derived from offshoring). These results are of considerable interest in light of the debate regarding the role of tax policy in determining the location of R&D activities by multinational firms. The results are consistent with the view that the location of R&D is amenable to the influence of tax subsidies at the margin. The coefficient associated with the average R&D tax price abroad is negative and significant, showing that a lower tax price abroad is correlated with a greater share of all technology stock being sourced from abroad. Correspondingly, local (home country) tax price is found to be positively related to the share of technology sourced from abroad, which implies that the higher the local tax price the more technology is sourced from offshore locations. The second stage results are presented in column (5). A Durbin-Wu-Hausman test supports the theoretical prediction that offshoring is likely to be endogenous (p=0.001). The coefficient associated with the offshoring share variable in the second stage equation is 1.478 and statistically significant. A 10-percent increase in the share of technology generated via offshoring is associated with 14.78-percent increase in productivity. The magnitude of the coefficient should be interpreted in reference to the distribution of offshoring share of patents. The overall sample mean is 6.8 percent with a standard deviation of 6.2 percent; though the within component of standard deviation is only 2.4 percent. (The "within" component reflects the extent of variation observed for a given industry in a given country over the study period, as opposed to the "between" component, which captures the variation between country-industry groups.) The standard deviation of year-on-year change in share of patents from abroad is one percent. In sum, an increase in foreign sourcing of 10 percent is a very large increase.

[Table 4 about here]

Although the FEIV estimates efficiently accommodate the possible issue of endogeneity of R&D offshoring (due to high performing sectors engaging in offshoring), the issue of dynamic panel bias remains, as does the possibility that input choices (capital stock and technology stock) may be endogenous. Table 5 presents GMM estimates to account for these issues. Column (1) and (2) report baseline estimates. Both capital stock per worker and technology stock per worker are identified via standard systems GMM instruments (differences in the level equation, and levels in the difference equation). Instrument matrix for column (1) includes foreign and domestic tax price measures in place of standard GMM instruments. In column (2) the share of patent stock generated through offshoring is also identified using the standard systems GMM approach. As can be seen, the results do not vary greatly between the two identification approaches. The results suggest that a 10-percent increase in the share of technology generated via offshoring will increase productivity by 4.91 percent.

The fact that the coefficient estimates vary between FEIV and GMM warrants consideration. We have seen that a 10-percent increase in share of patents sourced from abroad leads to a 4.91-percent increase in productivity according to GMM, or a 14.78-percent according to FEIV. First, we note that when the implied long run (steady state) effect is considered, the difference between the two estimates is substantially smaller; the GMM estimate is only a third less than the IV estimate.[10] In principle, GMM provides a suitable approach for accommodating the potential endogeneity but have been subject to criticisms associated with 'many weak instruments' (Stock *et al.* 2002, Bun and Windmeijer 2010). We argue that using foreign tax-price offers a powerful opportunity to cross-validate evidence generated using GMM. Tax policy

[10] For GMM the long run impact is given by: 4.9 / (1-0.843). For the FEIV estimates the long run impact factor is given by: 14.78 / (1-0.689).

provides a good candidate instrument. Numerous studies confirm that the location of R&D is amenable to tax subsidies. Moreover, the *a priori* case that foreign tax policy is exogenous to local productivity is strong and, notwithstanding the limitations of overidentification test statistics, these supports the case. We conclude that the best statistical approach is achieved by augmenting the instrument set in GMM with tax price variables, which we have shown perform well as external instruments.[11] At the same time, we limit the instrument set to three lags to ensure acceptable over-identification statistics (as suggested by Roodman 2006). We are reassured by the fact that the result is essentially robust across the two different identification strategies (FEIV and GMM). The effect is always positive and statistically significant, and potentially very strong economically. In our opinion, the productivity premium associated with R&D offshoring is closer to 5 percent than to 15 percent.

Column (3) reports the first of our robustness checks whereby we augment the model with both corporate income tax rate while controlling for local R&D tax price. The coefficients of interest are effectively unchanged which, we argue, provides further confidence that tax minimizing intellectual property migration is not unduly influencing our estimates.

We have argued previously that patents generated via offshored R&D but not filed in the home country are likely to represent adaptive, market-seeking R&D and are less likely to benefit the home country. Empirically testing this proposition is made complicated by the fact that the subset of patents derived from offshoring that are filed in the home country are highly correlated with total offshoring (correlation coefficient 0.94). In column (4) we report estimates of a model that includes both the share of technology stock from technology-seeking offshoring (patents invented abroad and also filed in the home country) and the share technology stock from

[11] Furthermore, the GMM estimates are closest to estimates available elsewhere. Castellani and Pieri (2013) suggest more modest gains from offshoring. They find that regions involved in offshoring have a 0.67 percentage point higher productivity growth. Our results are not directly comparable to theirs because they focus on offshoring *projects*.

market-seeking offshoring (patents invented abroad but not filed in the home country). The coefficient associated with market-seeking R&D offshoring is negative and significant. The estimate suggests that market-seeking R&D offshoring, which results in patents that are *not* filed at home, may detract from home-base productivity. This finding is consistent with Griffith *et al.* (2006) who find that locating inventors offshore has some cost absent of learning opportunities from large stocks of technology in the host country. This may relate to 'export' of high value-added activity (R&D) without countervailing benefits flowing back to home country in form of technology. Recall, however, that our measure of offshoring may fail to capture market-seeking type R&D in instances where the applicant of the resultant patent is the local subsidiary. This measurement error may bias the true effect of market-seeking R&D and we remain cautious not to overplay this finding.

Finally, the regression model in column (5) controls for industry-year fixed effect with little change to the quantitative nature of the results.

[Table 5 about here]

An important advantage of our industry level data is the exhaustive and global nature of the sample. It is widely considered that firms' benefits from offshoring may depend on the R&D occurring in a frontier country or perhaps even in the United States specifically. This may be cause for concern to policy makers in the United States, which is the home country to firms engaged the most in R&D offshoring. Using our data, we are able to test the extent to which the relationship between offshoring R&D and home-base industrial productivity may be driven by offshoring to any specific country. To flush out any above average impact of any particular host country we re-estimate the model 21 times, each time calculating a modified share of technology stock sourced from offshoring with a different host country omitted. The first panel of Table 6 reports estimates of the coefficient on share of technology stock from offshoring, each row reflecting a different country omitted (using model in column 1 of Table 5). These results show that no one single host country is driving the estimated parameter of interest. Put another way, in contrast to Griffith *et al.* (2006), we find nothing 'special' about offshoring to the United States, conditional on the outputs of the offshored R&D being filed in the applicant country (our measure of technology-seeking R&D offshoring).

[Table 6 about here]

We also considered the possibility that atypically large benefits from R&D offshoring by firms based in a specific home country may be driving the result. This may be the case if absorptive capacity that is crucial for establishing overall benefit is distributed unevenly. The second panel of Table 6 presents estimates of the model in column (1) of Table 5 sequentially dropping a different home country for each row. The estimated coefficient appears quite stable giving no indication that the result hinges on any particular home country. We also performed similar analysis using the full sample of countries but dropping one industry at a time and found no indication that the result is overtly influenced by the offshoring activities of any single industry (not reported).

We conducted a number of additional tests to investigate how technological differences between home and host countries moderate or condition local benefits from R&D offshoring. First, we examined whether offshoring to a country with apparent technological superiority provides more benefits. To measure technological capability, we estimate total factor productivity based on the residual of a simple OLS estimate of aggregate Cobb-Douglass Production function.[12] We then calculate the share of foreign sourced technology stock that is sourced from host countries where the subject industry has higher productivity than the

[12] As in the case of tax policy data, productivity could only be calculated for OECD member states, which is a minor limitation since OECD are the source of most technology generated via offshoring.

industry in the home country. This was not found to be significant (see results in column 1 Table 7). We experimented with alternative groupings of foreign sourced technology from countries a given level of productivity above the home country, but the results never indicated significance (not reported).

[Table 7 about here]

A second approach involved considering whether the benefits of offshoring vary according to the similarity of industrial structure of home and host country. To do this we first calculate the similarity of industrial structure of each pair of home and host countries based on the cosine distance of vector of technology stocks by industry (SIC). We then calculate the cosine weighted share of foreign sourced technology. Column (2) of Table 7 presents a model augmented with the ratio of cosine weighted average foreign sourced share divided by the simple average foreign sourced share. The coefficient is negative and significant, which suggests that the home country benefits most if offshoring occurs to a country that is more similar to the home country, relative to offshoring to a host that is relatively more different. We also examined whether the benefits vary systematically between high-tech and low-tech sectors. To do this we included foreign sourced share interacted with technology level (high, medium-high, medium-low and low, with low being the reference group). In this case, the technology intensity by sector is identified via OECD STAN Rev3 at the 2-digit level. The results are reported in column (3) of Table 7. The interaction with medium-low tech is weakly statistically significant, suggesting that the productivity effect may be larger for this group but the magnitude of the standard error cautions us not to overinterpret this finding. Furthermore, patents are a notoriously noisy measure of R&D activities in low-tech sectors.

Finally, we tested the robustness of the findings to the functional form of R&D offshoring. First, we investigated whether there might be non-linearities *à la* Castellani and Pieri (2013).

Results presented in column (4) of Appendix Table 7 suggest no such effect. Second, we varied the lags of R&D offshoring. Because our measure of offshoring is based on patent data, it follows by a few years the R&D investment decision. We believe that t-1 is an appropriate time lag since patent applications generally occur as an outcome of successful research activities. To further explore this issue, we estimated four additional models with lags t-2 to t-5, respectively. The results indicate that the observable impact appears greatest in t-1 and t-2 and diminishes, albeit weakly, thereafter (not reported).

Before offering concluding comments, we consider the remaining limitations. First, while we provide a representative view of the average benefits reflecting the net impact on local industry, including both private and spillover benefits and losses, the industry level approach provides no new evidence on the mechanism(s) through which offshored R&D translates into productivity improvements at home. These have been studied elsewhere and are complementary to our finding (*e.g.*, Harhoff *et al.* 2014). Direct analysis of the extent of spillovers would be worthwhile and best undertaken using firm level data. Similarly, there might be other mechanisms at play than spillovers. If firms engaged in R&D offshoring are larger than other firms, aggregate effects could be driven simply by the weights of these firms in their home industries. Moreover, if R&D offshoring allows firms to expand and increase their market shares, aggregate effects may be driven by a reallocation of resources from the least productive firms (less likely to engage in R&D offshoring) towards the more productive firms. We are also aware that our findings do not necessarily apply to the service industry, which is notably not well served by patents, as well as to other industries where patents are not intensively used (see Cohen *et al*. 2000). Second, we expect that, in part, our results reflect a higher cost of offshored R&D (though low value patents are filtered out). Irrespective, our results newly confirm that the home country—not just the firm—benefit from offshoring and indicate that benefits are not contingent on the specific host locations. Finally, we are keenly aware that any instrumental variable estimation is open to fundamentally untestable criticism regarding the veracity of the assumption of exogeneity. We have argued that the *a priori* case that foreign R&D tax subsidies is exogenous to domestic productivity is sound and, this appears to be borne out by standard overidentification tests, notwithstanding their inherent limitations. We are perhaps most reassured by the fact that result appears robust across two different identification strategies (IV and GMM).

Conclusion

The potential for R&D offshoring to weaken the home country technological capabilities and the loss of productivity spillovers compromising long-term growth has concerned policy makers for a long time. We have investigated this concern using new industry-level data covering almost three decades. We employed an identification strategy that accommodates the potential simultaneity between industrial performance and offshoring.

Our fundamental contribution is furnishing new evidence that the home country—not just the firm—can benefit from R&D offshoring. Results show that R&D offshoring can induce long-term productivity benefits for home-country industrial actors at large. However, we find that home country benefits hinge on the nature of offshoring. The results suggest that only technology-seeking R&D translates into productivity gains. This finding extends the managerial literature on international technology sourcing, which argues *inter alia* that only the most advanced R&D improves the focal firm's performance (*e.g.*, Singh 2008, Añón Higón *et al.* 2011, Cantwell and Piscitello 2013, Rahko 2016). It is also consistent with the arguments made by previous scholars that the benefits of market-seeking R&D offshoring will primarily be restricted to host country markets.

We find no evidence that benefits are restricted to industries offshoring to the United States—or any other particular host country in our sample. This supports the view that firms themselves are best placed to choose the location of R&D that will generate technological advantage and equally that the globally dispersed technology frontier is difficult to capture using aggregate national indicators.

Our results help to reconcile traditional fears concerning the impact of R&D offshoring on home economies with the enduringly strong economic performance of those countries most heavily engaged in the activity—the United States and Switzerland are among the handful of OECD countries that offshore more R&D than they host and they are also among the most productive, technologically advanced economies (Thomson 2013). We hope that in this light, our results might give pause for thought to policy makers who may otherwise be tempted to offer inducements to curb offshoring.

Naturally, more research is needed in order to understand more detailed patterns of the geographical distribution of benefits and the extent of spillovers to other firms in the home country. Similarly, R&D offshoring is just one feature of the national innovation system and its benefits may be conditioned by other equally important features. For instance, the benefits may be enhanced in countries with strong local manufacturing capabilities or in which MNEs are better integrated into the local innovation network.

In this regard, we hope that the methodological contribution advanced in this paper may contribute to future works. Specifically, we have provided first-of-its-kind validation test of the use of patent data as a measure of R&D offshoring, making use of the origin country of applicants and inventors. Moreover, the results suggest that filing patterns provide useful information about the geography of benefit arising from patented technology and, more speculatively, a means of distinguishing between market-seeking and technology-seeking R&D activities. Future firm-level analysis could be particularly promising in elucidating a better understanding about multinational enterprise technology strategies and how these map into patent filing patterns.

References

Añón Higón, D., Manjón Antolín, M., & Mañez, J. A. (2011). Multinationals, R&D, and productivity: evidence for UK manufacturing firms. *Industrial and Corporate Change*, *20*(2), 641–659.

Arvanitis, S., & Hollenstein, H. (2011). How do different drivers of R&D investment in foreign locations affect domestic firm performance? An analysis based on Swiss panel micro data. *Industrial and Corporate Change*, *20*(2), 605–640.

Bartlett, C. A., & Ghoshal, S. (2000). Going global: Lessons from late movers. *Harvard Business Review* (March-April 2000), 132–142.

Ali-Yrkkö, J., & Rouvinen, P. (2015). Slicing up global value chains: a micro view. *Journal of Industry, Competition and Trade*, *15*(1), 69–85.

Bloom, N., & Griffith, R. (2001). The Internationalisation of UK R&D. *Fiscal Studies*, *22*(3), 337–355.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Breunig, R., & Wong, M. H. (2008). A richer understanding of Australia's productivity performance in the 1990s: Improved estimates based upon firm-level panel data. *Economic Record*, *84*(265), 157–176.

Bun, M. J., & Windmeijer, F. (2010). The weak instrument problem of the system GMM estimator in dynamic panel data models. *The Econometrics Journal*, *13*(1), 95–126.

Criscuolo, P. (2009). Inter-firm reverse technology transfer: the home country effect of R&D internationalization. *Industrial and Corporate Change*, *18*(5), 869–899.

Cantwell, J. (1995). The globalisation of technology: What remains of the product cycle model? *Cambridge Journal of Economics*, *19*(1), 155–174.

Cantwell, J., & Piscitello, L. (2013). Historical changes in the determinants of the composition of innovative activity in MNC subunits. *Industrial and Corporate Change*, *23*(3), 633–660.

Castellani, D., & Pieri, F. (2013). R&D offshoring and the productivity growth of European regions. *Research Policy*, *42*(9), 1581–1594.

Ciaramella, L. (2017). Patent Boxes and the Relocation of Intellectual Property. SSRN Working Paper no 2943435.

de Rassenfosse, G., Dernis, H., & Boedt, G. (2014). An introduction to the Patstat database with example queries. *Australian Economic Review*, *47*(3), 395–408.

de Rassenfosse, G., Dernis, H., Guellec, D., Picci, L., & van Pottelsberghe de la Potterie, B. (2013). The worldwide count of priority patents: A new indicator of inventive activity. *Research Policy*, *42*(3), 720–737.

Dunning, J. H. (1994). Multinational enterprises and the globalization of innovatory capacity. *Research Policy*, *23*(1), 67–88.

European Commission (2012). Internationalisation of business investments in R&D and analysis of their economic impact. *European Commission* document No. EUR 25195 EN.

Griffith, R., Harrison, R., & Van Reenen, J. (2006). How special is the special relationship? Using the impact of US R&D spillovers on UK firms as a test of technology sourcing. *American Economic Review*, *96*(5), 1859–1875.

Griliches, Z., (1979). Issues in assessing the contribution of research and development to productivity growth. *The Bell Journal of Economics*, 92–116.

Griliches, Z. (1986). Productivity, R&D, and basic research at the firm level in the 1970's. *American Economic Review*, *76*(1), 141–154.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, *28*(4), 1661–1707.

Guellec, D., & van Pottelsberghe de la Potterie, B. (2001). The internationalisation of technology analysed with patent data. *Research Policy*, *30*(8), 1253–1266.

Harhoff, D., Mueller, E., & Van Reenen, J. (2014). What are the channels for technology sourcing? Panel data evidence from German companies. *Journal of Economics & Management Strategy*, *23*(1), 204–224.

Harhoff, D., Scherer, F. M., & Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, *32*(8), 1343–1363.

Hines, J. (1993). On the sensitivity of R&D to delicate tax changes: The behavior of U.S. multinationals in the 1980s. In: A. Giovannini, R. Glenn Hubbard, and J Slemrod (eds), Studies in International Taxation. Chicago: University of Chicago Press.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, *108*(3), 577–598.

Jaffe, A. B., & de Rassenfosse, G. (2017). Patent citation data in social science research: Overview and best practices. *Journal of the Association for Information Science and Technology*, 68(6), 1360–1374.

Kumar, N. (2001). Determinants of location of overseas R&D activity of multinational enterprises: the case of US and Japanese corporations. *Research Policy*, *30*(1), 159–174.

Lall, S. (1979). The International Allocation of Research Activity by US Multinationals. *Oxford Bulletin of Economics and Statistics*, *41*(4), 313–331.

Le Bas, C., & Sierra, C. (2002). 'Location versus home country advantages' in R&D activities: some further results on multinationals' locational strategies. *Research policy*, *31*(4), 589–609.

McFetridge, D. G. and J. P. Warda (1983). Canadian R&D Incentives: Their Adequacy and Impact, Canadian Tax Paper No. 70. Toronto, Canadian Tax Foundation.

Mansfield, E., Teece, D., & Romeo, A. (1979). Overseas research and development by US-based firms. *Economica*, *46*(182), 187–196.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica, 49*(6), 1417–1426.

NSF 2010 (http://www.nsf.gov/statistics/infbrief/nsf10322/)

OECD (2002). Frascati Manual 2002 – Proposed Standard Practice for Surveys on Research and Experimental Development. OECD: Paris, 256 pages. ISBN:9789264199033.

OECD (2009), Patent statistics manual, Paris

OECD (2011), *STAN indicators*, STAN: OECD Structural Analysis Statistics (database).

Olley, G. S., and A. Pakes. 1996. The dynamics of productivity in the telecommunications equipment industry. *Econometrica* 64: 1263–1297.

Patel, P., Pavitt, K., 1988. The international distribution and determinants of technological activities. *Oxford Review of Economic Policy* 4, 35–55.

Patel, P., & Vega, M. (1999). Patterns of internationalisation of corporate technology: location vs. home country advantages. *Research Policy*, *28*(2), 145–155.

Picci, L. (2010). The internationalization of inventive activity: A gravity model using patent data. *Research Policy*, *39*(8), 1070–1081.

Porter, M. E. (1990), *The Competitive Advantage of Nations*. New York, Macmillan Inc.

Rahko, J. (2016). Internationalization of corporate R&D activities and innovation performance. *Industrial and Corporate Change*, 25(6), 1019–1038.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, *9*(1), 86–136.

Schmoch, U., Laville, F., Patel, P., & Frietsch, R. (2003). Linking technology areas to industrial sectors. Final report to the European Commission - DG Research.

Singh, J. (2008). Distributed R&D, cross-regional knowledge integration and quality of innovative output. *Research Policy*, *37*(1), 77–96.

Song, J., & Shin, J. (2008). The paradox of technological capabilities: a study of knowledge sourcing from host countries of overseas R&D operations. *Journal of International Business Studies*, *39*(2), 291–303.

Song, J., Azakawa, K., Chu, Y., 2011. What determines knowledge sourcing from host locations of overseas R&D operations? A study of global R&D activities of Japanese multinationals. *Research Policy* 40, 380–390.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, *20*(4), 518–529.

Thomson, R. (2013). National scientific capacity and R&D offshoring. *Research Policy*, *42*(2), 517–528.

Thomson, R., (2017) The Effectiveness of R&D tax credits, *Review of Economics and Statistics, 99*(3), 544–549.

Vernon, R. (1966). International investment and international trade in the product cycle. *Quarterly Journal of Economics*, *80*(2), 190–207.

Webb, C., Dernis, H., Harhoff, D., & Hoisl, K. (2005). Analysing European and international patent citations, *OECD Science, Technology and Industry Working Papers*, No. 2005/09, OECD Publishing, Paris.

Wilson, D. J. (2009). Beggar thy neighbor? The in-state, out-of-state, and aggregate effects of R&D tax credits. *Review of Economics and Statistics*, *91*(2), 431–436.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics*, *126*(1), 25–51.

Appendix

An important contribution of the present paper is to propose a new way of identifying patents arising from technology (vs. market)-seeking foreign R&D. By definition, market-seeking activities target local markets. Hence, inventions arising from such activities are less likely to be protected in the home country than inventions arising from technology-seeking activities.

The present approach departs from previous work. In a seminal paper, Frost (2001) uses the geographical origin of patent citations to determine the type of foreign R&D. The author cross-referenced all patents issued between 1980 and 1990 to U.S.-based greenfield subsidiaries with each of the prior patents it cites as a reference—as a way of capturing the geographic origin of the technical ideas embodied in U.S. subsidiaries' innovations.

Because the present study considers patent applications for a large number of jurisdictions, we cannot rely on citation data. The coverage of citation data in the PATSTAT database is highly uneven across patent offices, and more importantly citation practices vary widely across offices (*e.g.*, Jaffe and de Rassenfosse 2017). Our measure has the desirable properties of being available for all countries and robust to country-differences in patenting practices and in data coverage.

In order to compare to the extent possible the proposed measure with prior work, we undertook additional analysis using patents filed at the USPTO to examine the relationship between a citation-based approach and our "filing behavior" approach. For that purpose, we collected from the PATSTAT database all patents filed at the USPTO in a given year (2010) as well as all the patents that they cite. We then collected information on:

- The country of residence of assignees and inventors, for both the focal citing patents and the cited patents;

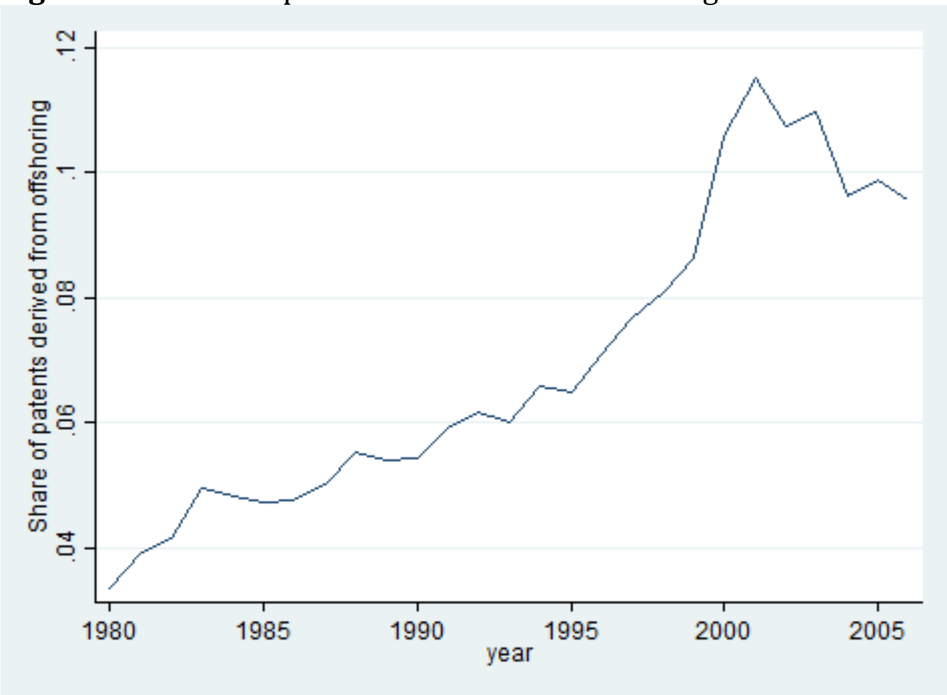
- Whether the focal patents result from offshoring activities (= 1 if assignees and inventors reside in different countries);
- Whether the focal patents were also filed at home (= measure of technology-seeking R&D);
- Whether the focal patents cite local knowledge (= 1 when an offshored patent invented in country A cites another patent also invented in country A).

Next, we test econometrically whether offshored patents that cite local inventors are also more likely to be filed in the residence country of the applicant using a linear probability model. We do this for all applicant countries. The results of the regressions are summarized in the Figure below. It shows, for instance, that offshored patents invented in Austria (AT) are more likely to cite local knowledge if they are filed in Austria. However, the effect is not statistically significant. Bars reported in blue indicate effects statistically significantly different from zero (5% probability threshold).

[Figure A1 about here]

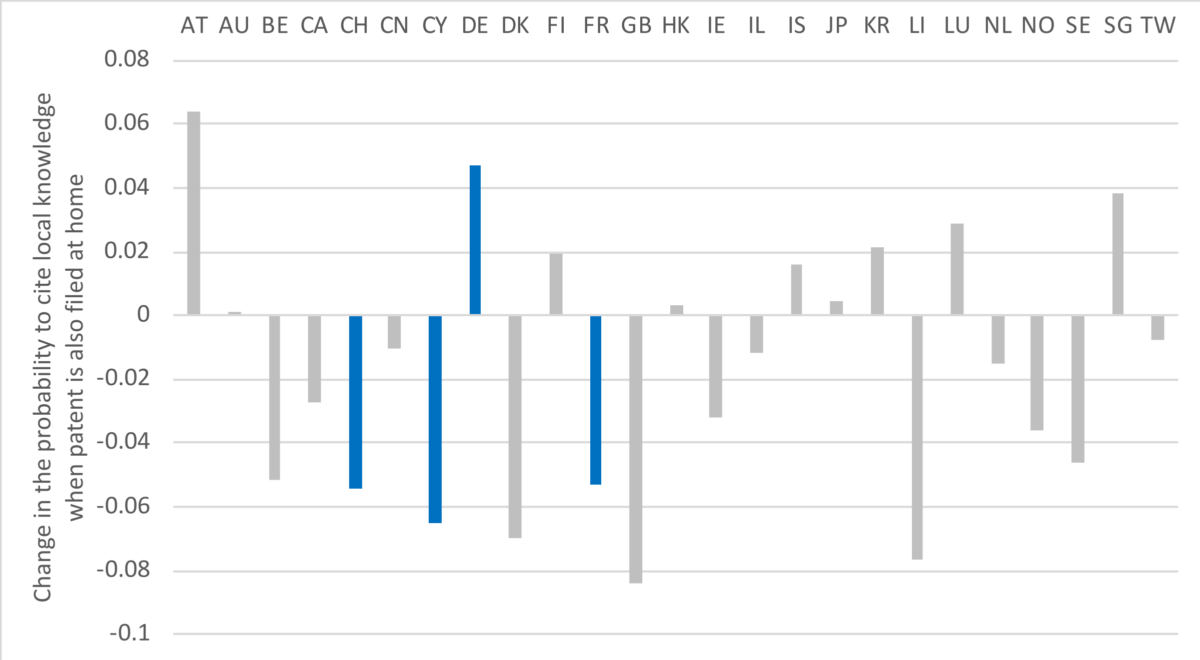
Overall, it emerges that the two measures are fairly unrelated. No clear pattern emerges from the data, and the effect size is quite small (and so is the share of variance explained). Coefficients vary from a minimum of -0.08 to a maximum of 0.06. We believe that this heterogeneity primarily reflects differences in citation practices across jurisdictions. Indeed, comparing citations across the USPTO and the EPO, two well-studied jurisdictions, is already challenging, as argued in Webb *et al.* (2005). This lack of correlation may also be explained by the fact that all the focal patents in our sample are filed at the USPTO by design—offshored patents in this sample were thus valuable enough to be filed at the USPTO, and are therefore also more likely to originate from technology-seeking R&D. Further research, particularly survey-based research, would be valuable to better understand this issue.

Figure 1. Percent of patents derived from offshoring



Notes: filed in applicant country and family size greater than one.

Figure A1. Overview of econometric regression results



Notes: The bars represent the percentage change in the probability that a U.S. patent from a given home country (*e.g.*, AT) cites local patents (*i.e.*, AT) when the patent is also filed at home (*i.e.*, AT). Bars in blue denote coefficients that are significant at the 5% probability threshold.

Table 1. Overall sample of patents observed

	Total	Derived from offshoring
Total priority patents	4,173,233	182,144
Filed in 2+ countries	1,631,132	133,189
Filed in 2+ countries *and* filed in the home (applicant) country	1,606,887	121,545

Notes: "derived from offshoring" identified with applicant / inventor from different countries.

Table 2. Correlation between offshored patents and R&D financed from abroad

	Panel A. Country analysis				*Panel B. Country-industry analysis*			
Method:	Pooled OLS		Fixed effects		Pooled OLS		Fixed effects	
log of foreign-financed R&D in t-1	0.625**	0.330**	0.119**	0.104**	0.335**	0.156**	0.018	0.026*
	[0.080]	[0.092]	[0.053]	[0.039]	[0.046]	[0.034]	[0.011]	[0.012]
log of foreign-financed R&D in t-2		0.313**		0.055		0.183**		0.005
		[0.044]		[0.044]		[0.025]		[0.016]
Constant	1.580**	1.504**	2.981**	2.898**	0.703	1.116**	0.523**	0.815**
	[0.398]	[0.489]	[0.227]	[0.245]	[0.350]	[0.363]	[0.188]	[0.074]
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	740	612	740	612	3,053	1,896	3,053	1,896
R-squared [(a)]	0.62	0.63	0.66	0.66	0.24	0.23	0.37	0.37
Number of groups	-	-	40	37	-	-	401	297

Notes: Time effects captured with decade dummies. The dependent variable is the log number of offshored patents in year *t*. Standard errors clustered at the country level in parenthesis.
**: p-value < 0.01. *: p-value < 0.05
[(a)] 'Within' R-squared reported in fixed effect specifications.

Table 3. Data Summary

Variable	Mean	Std. Dev.	Min	Max
Output per worker (‘000s USD)	84.3	80.1	6.1	1236.1
Capital per worker (‘000s USD; PIM w. 5% depreciation)	138.3	195.1	0.244	2375.5
Technology stock (‘000s patents, PIM w. 15% depreciation)	840.7	2525.3	0.127	40436.3
Share of technology stock derived from offshoring	6.8	6.23	0.120	56.0

Notes: N = 7721; “PIM” stands for Perpetual Inventory Method.

Table 4. OLS and IV regression results (dependent variable: log of output per worker)

VARIABLES	(1) OLS	(2) OLS	(3) FE	(4) IV 1st stage	(5) FE IV
Output per worker (log) $_{t-1}$		0.942***	0.693***	0.00221*	0.689***
		[0.00868]	[0.00831]	[0.00121]	[0.00851]
Capital per worker (log) $_{t-1}$	0.303***	0.0158***	0.00988**	0.00287***	0.00619
	[0.00692]	[0.00351]	[0.00423]	[0.000618]	[0.00445]
Technology stock (log) $_{t-1}$	0.0467***	0.00200**	0.00794	-0.0209***	0.0336***
	[0.00233]	[0.000982]	[0.00782]	[0.00111]	[0.0113]
Tech. share derived from offshoring $_{t-1}$	1.644***	0.153***	0.240***		1.478***
	[0.110]	[0.0551]	[0.0790]		[0.396]
Average tax price abroad $_{t-2}$				-0.129***	
				[0.0285]	
Local R&D tax price$_{t-2}$				0.111***	
				[0.00646]	
Overidentification[a]	-	-	-	-	0.166
R-squared			0.681	0.396	0.670

Notes: N=7,721. All models control for year effects and time invariant unobserved heterogeneity at the country-industry level (444 groups). First stage Cragg-Donald F statistic for FE IV is 155. Overidentification for FE IV (column 4) presents Sargan-Hansen p-value. Within R-Squared provided for FE estimates (columns 3–5).

Table 5. GMM regression results (dependent variable: log of output per worker)

VARIABLES	(1) GMM	(2) GMM	(3) GMM	(4) GMM	(5) GMM
Output per worker (log) $_{t-1}$	0.843***	0.840***	0.832***	0.855***	0.816***
	[0.0299]	[0.0306]	[0.0299]	[0.0282]	(0.0284)
Capital per worker (log) $_{t-1}$	0.00782	0.0112*	0.0157***	0.0118**	0.0352***
	[0.00520]	[0.00594]	[0.00597]	[0.00559]	(0.00921)
Technology stock (log) $_{t-1}$	0.0187***	0.0147***	0.0158***	0.0118***	0.0152**
	[0.00406]	[0.00383]	[0.00404]	[0.00354]	(0.00676)
Tech. share derived from offshoring $_{t-1}$	0.491**	0.447***	0.419**	0.456***	0.605*
	[0.213]	[0.150]	[0.168]	[0.145]	(0.310)
Local R&D tax price$_{t-1}$			-0.0434		
			[0.0432]		
Corporate income tax rate$_{t-1}$			-0.0206		
			[0.0153]		
Tech. share from offshoring not filed in applicant country $_{t-1}$				-0.799**	
				[0.390]	
Country-year fixed effects	No	No	No	No	Yes
Overidentification[a]	0.10	0.29	0.26	0.98	0.447
1st, 2nd serial correlation	0.00,0.51	0.00, 0.51	0.00, 0.51	0.00, 0.51	0.00, 0.89

Notes: N=7,721. All models control for year effects and time invariant unobserved heterogeneity at the country-industry level (444 groups). Country-year fixed effects are controlled by demeaning all variables by the country-year averages prior to implementation of GMM. Estimates use the asymptotically efficient two-step procedure applying Windmeijer's (2005) correction to the standard errors. All right hand side variables instrumented. For column (1) instrument matrix include foreign and domestic tax price measures in place of standard GMM instruments. For column (2) instrument matrix *also* includes standard GMM instruments. Instrument count is constrained by limiting lagged instruments to t-3. Overidentification for GMM results present Hansen statistic p-value reported using Stata xtabond2 (Roodman 2009).

Table 6. Coefficient estimates of share of technology from offshoring.

Omitted country	**Tests omitting R&D offshoring to each *host* in calculation of offshoring share**		**Tests omitting each home country in turn**		
	Coeff	s.e.	Coeff.	s.e.	Obs.
AT	0.381***	[0.109]	0.372***	[0.108]	7,766
BE	0.407***	[0.122]	0.393***	[0.110]	7,901
CA	0.376***	[0.109]	0.360***	[0.109]	7,946
CZ	0.386***	[0.108]	0.360***	[0.108]	8,096
DE	0.463***	[0.141]	0.367***	[0.109]	7,766
DK	0.390***	[0.108]	0.342***	[0.103]	7,978
ES	0.383***	[0.108]	0.403***	[0.111]	8,006
FI	0.372***	[0.110]	0.331***	[0.0986]	7,768
FR	0.461***	[0.127]	0.392***	[0.111]	8,127
GB	0.410***	[0.140]	0.378***	[0.108]	7,768
GR	0.388***	[0.108]	0.366***	[0.110]	8,129
HU	0.384***	[0.108]	0.390***	[0.112]	8,104
IE	0.385***	[0.108]	0.308***	[0.110]	8,031
IT	0.332***	[0.0962]	0.379***	[0.111]	7,796
KR	0.384***	[0.108]	0.430***	[0.110]	8,166
NL	0.417***	[0.125]	0.411***	[0.112]	7,907
NO	0.384***	[0.109]	0.354***	[0.106]	7,870
PL	0.385***	[0.108]	0.378***	[0.109]	8,078
PT	0.384***	[0.108]	0.323***	[0.0940]	8,258
SE	0.383***	[0.109]	0.379***	[0.111]	7,942
US	0.431***	[0.120]	0.390***	[0.109]	7,766

The dependent variable is output per worker. All models control for year effects and time invariant unobserved heterogeneity at the country-industry level (444 groups). GMM estimates use the asymptotically efficient two-step procedure applying Windmeijer's (2005) correction to the standard errors. All right hand side variables instrumented for GMM. Instrument count is constrained by limiting lagged instruments to t-3.

Table 7. Additional Robustness Tests

VARIABLES	(1)	(2)	(3)	(4)
Output per worker (log) $_{t-1}$	0.850***	0.855***	0.867***	0.846***
	(0.0289)	(0.0277)	(0.0273)	(0.0291)
Capital per worker (log) $_{t-1}$	0.0115**	0.0112**	0.00916*	0.0127**
	(0.00560)	(0.00523)	(0.00487)	(0.00617)
Technology stock (log) $_{t-1}$	0.0140***	0.0147***	0.0116***	0.0135***
	(0.00364)	(0.00333)	(0.00336)	(0.00360)
Tech. share derived from offshoring $_{t-1}$	0.445***	0.504***	0.570**	0.228
	(0.150)	(0.143)	(0.224)	(0.241)
Tech. share derived from offshoring to more productive countries $_{t-1}$	-0.211			
	(0.164)			
Cosine weighted share of foreign sourced technology $_{t-1}$		-0.605**		
		(0.293)		
Tech. share derived from offshoring $_{t-1}$ squared				0.436
				(0.868)
Tech. share derived from offshoring $_{t-1}$ × high tech			0.121	
			(0.154)	
Tech. share derived from offshoring $_{t-1}$ × medium-high tech			-0.0236	
			(0.149)	
Tech. share derived from offshoring $_{t-1}$ × medium-low tech			0.351*	
			(0.195)	
Observations	7,721	7,721	7,721	7,721