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What determines international and inter-sectoral knowledge diffusion? An analysis based on patent citations, technological distance and spillovers

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Abstract

This paper studies antecedents of knowledge flows as measured by patent forward citations that occur between "input" and "output sector-countries". More concretely, we look at R&D spillovers and technological distance between sector-countries. For this purpose, we develop a knowledge flow matrix similar to input-output tables in trade. We estimate a gravity model with typical gravity variables, also adding technological distance and R&D spillover variables for several internal and external sources. Our results indicate that involuntary knowledge exchange between input and output sector-countries is sustained leading to even larger knowledge diffusion to the output sector. In sum, both knowledge spillovers from the output sector-country and from external sector-countries have a large impact on further knowledge flows between the input output sector-country pair. External knowledge is particularly useful if it comes from high-tech industries. We detect a large heterogeneity across industries: In general, the knowledge diffusion that is based on patents in low-tech industries can benefit from knowledge generated in high-tech industries. In contrast, high-tech industries' diffusion cannot benefit from knowledge from low-tech industries. Technological distance between sector-countries has a negative impact on further knowledge flows so that only technologically proximate sector-countries can benefit from spillovers.

Jelcodes:O33,O34

1 Introduction

According to Jaffe et al. (1993) [15], patent citations can be seen as a paper trail of knowledge flows among firms in an industry. Patent citations open up the possibility of tracing multiple linkages and spillovers between inventions, inventors, scientists, firms, and locations. In addition, they allow for creating indicators of the importance or technological impact of patents (Jaffe and Trajtenberg, 2002, p. 3) [14]. On a more aggregated level, patent citations enable us to study technological linkages between countries and technological fields (and corresponding industries). Although there has been quite substantial work on patent citations since the NBER patent citations project, linkages between countries and industries and spatial patterns of knowledge flows are still under researched or are quite limited with respect to the number of countries or industries considered. Especially in international trade literature, the focus is more on geographical patterns of trade flows and the technological space is very often neglected. Peri (2005, p. 309) [30]recognized that there is a mismatch between theory and empirics in the trade-growth literature in its analysis of international knowledge flows.

In this paper, we study the technological antecedents of knowledge diffusion as measured with patent citations. More concretely, we study the effect of absorptive capacity and knowledge spillovers arising from other industries' and countries' R&D stocks on the number of forward citations that a focal sector-countries' patent applications receive from another sector-country. We do this in a gravity-like model where we analyze input and output factors that are important in the innovation process and for bringing out potentially high-value patents that are cited by future patent filings. In addition, we control for industry- and country-specific factors that might influence the technological performance. For this purpose, we emulate World Input Output Tables by counting the number of forward citations that patents of various sector-countries (input dimension) receive from other sector-countries (output dimension).

Beginning with Peri (2005) [30] and Maurseth and Verspagen (2002) [23], there are now more and more papers studying international knowledge flows as embodied in patent citations in gravity models (e.g., Li, 2014 [18], Morescalchi et al., 2015 [26]). A new element of this paper is that we are analyzing knowledge flows at a much more detailed level, namely at the sector-country level with both an input and output dimension. Furthermore, we do not only focus on variables reflecting geographical distance at country level, but also technological distance at the sector level. The paper contributes in bridging the gap between the aforementioned macro-oriented studies and microlevel studies such as those by Jaffe (1986) [13], Jaffe and Henderson (1993) [15] and Bloom, Schankerman and van Reenen (2013) [4].

A further new element of this study is that we study the impact of knowledge spillovers stemming from the own sector-country, the output sector-country and other "external" sector-countries on future knowledge flows to the output sector-country. To the best of our knowledge, we are the first to do so in a gravity-like model. As already said, we shift the lens of analysis from variables that are relevant in the basic gravity model such as distance and borders to variables that are important in the process of knowledge acquisition and sequential innovation. We propose that absorptive capacity, intra- and interindustry spillovers and domestic and foreign spillovers are important determinants of outgoing knowledge flows (that is knowledge that is used by other sectors or countries) and that technological distance between these sectors reduces interindustry knowledge flows.

We use all published patent applications from 1995 until 2005 that are available in the EPO Worldwide Patent Statistical Database (PATSTAT, EPO, 2013) [7] to calculate the number of forward citations for each country-sector pair. Our results indicate that input-output relationships are very important in determining future knowledge flows between the input-output country-sectors. Knowledge spillovers from the output sector are even more important than knowledge accumulated in the own sector-country. Knowledge spillovers from external sector-countries outside the input-output relationship are also very important, but they are not complementary to spillovers from the output sector. Their effect rather depends on the technological advancement of the respective input sector. Technological distance between sectors is found to be a major impediment of future knowledge flows between sector-country pairs.

The paper is structured as follows: Section 2 gives a literature review on the use of patent citations as indicators of knowledge flows and empirical work on knowledge spillovers and states or hypotheses. Section 3 presents our empirical model. Section 4 describes the data we use and the variables. Section 5 discusses the estimation strategy. Section 6 presents the results and Section 7 concludes.

2 Hypotheses

2.1 The effect of spillovers

In literature, there is a growing interest in analyzing knowledge spillovers as measured by patent citations in geographic space both at regional and international level. In general, literature can be divided into two broad streams: The literature on localization of knowledge spillovers that often uses matched control samples with patent citations (Jaffe et al., 1993 [15]; Murata et al., 2014 [28]) and on international spillovers that is often analyzed within a gravity model. The latter stream of literature is still mainly concerned about the effect of distance and borders as in traditional gravity models. Exceptions are Mancusi (2008) [22] and Mukherji and Silberman (2013) [27] who studied the effect of absorptive capacity and spillovers on patents resp. citation flows. In the context of spillovers, it is important for the recipient country to understand and exploit external knowledge. A country's and industry's ability to exploit knowledge resources might depend on past experience with R&D activities, an idea that is commonly referred to as absorptive capacity (Cohen and Levinthal, 1989) [5]. In our study, these past R&D experience is proxied by the focal sector-country's R&D stock. In contrast, spillovers is usually knowledge that spills from competitors, other industries or countries. More concretely, an R&D project or – more general – R&D activities at a more aggregated level may produce knowledge that can be useful to another firm, industry or country in doing its own research. According to Hall et al. (2010) [11], the more knowledge is codified and the higher is the absorptive capacity of other firms, the more knowledge spillover will take place. We can distinguish between incoming spillovers and outgoing spillovers both measured with international and inter-sectoral patent citations where we interpret outgoing knowledge as technological diffusion. More concretely, we analyze the effect of other countries' and sectors' knowledge stocks weighted with incoming knowledge on the number of citations that the focal country's/sector's patent applications receive. We expect that incoming knowledge resp. existing internal knowledge determines knowledge diffusion to a large extent. Our proposition is related to trade literature where firms engaging in trade relationships are found to enhance knowledge diffusion (Keller, 2004; MacGarvie, 2006) [16] [20]. Interestingly, given the importance of knowledge diffusion, there have been little to attempts to study the effect of former technological relationships rather than trade relationships. In this paper, we analyze prior knowledge exchange that might lead to further knowledge diffusion.[1]

[1] If we speak of knowledge exchange in this paper, we only refer to "involuntary" knowledge exchange based on spillovers and not formal knowledge exchange that is based on cooperation or licensing agreements etc.

Hypothesis 1a: Both absorptive capacity and knowledge spillovers from the output sector-country exert a positive impact on further knowledge diffusion measured by the number of forward citations that the input sector-country receives from the output sector-country.
Hypothesis 1b: Knowledge spillovers from external sector-countries (i.e. sector-countries that are not part of the input-output relationship) exert a positive impact on further knowledge diffusion between the input and output sector-country.

2.2 Technological distance

Technological distance between countries and industries is an important concept in new-growth theories (Romer, 1990, Grossman and Helpman, 1991) [31] [10] and has been often applied empirically by using differences in total factor productivity, e.g. between leading countries and laggards (e.g., Aghion et al. 2005) [1]. It has been also put at micro level by measuring technological proximities between firms, e.g. based on their patent portfolios (Jaffe, 1996) [13]. The basic expectation is that larger technological distance between economic entities decrease the probability and the extent of outgoing knowledge spillovers that might occur between them and can be appropriated by the receiving sector-country. More concretely, the larger technological distance is, the less likely spillovers and further knowledge diffusion to occur. Consequently, we expect that larger technological distance between sectors or countries leads to less knowledge flows between them.

Hypothesis 2: Technological distance between sectors/countries has a negative impact on knowledge diffusion, i.e. it decreases the number of citations that an input sector/country receives from an output sector/country.

2.3 Low-tech vs. high-tech sectors

Accumulated spillovers from external sector-countries might stem from sector-countries that are quite heterogeneous technologically. A further distinction among incoming external knowledge is useful both theoretically and empirically. In innovation and growth literature, high-tech countries or "technological leaders" are considered main growth and technological drivers. Mancusi (2008) [22] found that only spillovers from technologically leading countries are effective in increasing innovative output. Peri (2005) [30] found that research across regions is rather concentrated and they argue that technologically leading regions may therefore act as learning sources for other regions. What is missing to a large extent in existing literature is the sectoral dimension [2]. Similar to countries or regions, leading high-tech sectors might also act as learning source for others. Hence, we argue that knowledge spillovers from external sector-countries should only have a positive effect on knowledge flows when the external sector is high-tech.

Hypothesis 3: Accumulated knowledge spillovers from external sector-countries only exert a positive impact on further input-output knowledge diffusion if they come from external high-tech sectors.

Griffith et al. (2004) [9] studied the effect of absorptive capacity on productivity for OECD sector-countries. They found that sector-countries lagging behind the technological frontier catch up particularly fast if they invest heavily in R&D, i.e., the further a country lies behind the frontier, the

[2] Exceptions are Keller (2002) [17], Frantzen (2002) [8], Park (2004) [29], and Malerba et al. (2013) [21]. They all examine intersectoral, intrasectoral, national and international spillovers. However, except for Malerba et al., all studies examine the impact of these spillovers on total factor productivity and not on knowledge flows

greater the potential for R&D to increase growth of total factor productivity through technology transfer from more advanced countries. Tsai and Wang (2004) [35] found evidence of an R&D spillover effect from the high-tech sector into traditional manufacturing industries in Taiwan. In our context, we also expect that low-tech sectors can learn from R&D generated in high-tech sectors, but not the other way round. Consequently, low-tech sector-countries are expected to be cited more often when the output sector is high-tech.

Hypothesis 4a: When the input sector is low-tech and the output sector is high-tech, we expect a positive spillover effect from the high-tech sector on the number of forward citations between the input and output sector, i.e. knowledge genereated in high-tech setors is first learnt by low-tech sectors before flowing back to high-tech sectors.
Hypothesis 4b: When the input sector is high-tech and the output sector is low-tech, we do not expect to find any spillover effect from the low-tech sector on further knowledge diffusion.

Finally, we combine our arguments stated in hypotheses 3 and 4 with respect to high-tech vs. low-tech sectors by including both the output and external spillover dimension. However, from the reasoning above, it is not clear whether the learning effect or the effect arising from absorptive capacity dominates. The first effect refers to sectors that are farther away from technological frontier and that should benefit most since scope for learning is highest there. The second effect refers to sectors closer to the frontier having a higher absorptive capacity so that they may benefit more from spillovers (see Aghion et al., 2009 [2], and Migulez and Moreno, 2015 [25], for a similar reasoning).

Hypothesis 5: From the outset, it is not clear whether accumulated knowledge spillovers from external high-tech sector-countries exert a positive impact on further input-output knowledge diffusion only for low-tech, only for high-tech or for both low-tech and high-tech output sector-countries.

3 The empirical model

Essentially, we extend the models proposed by Mancusi (2008) [22] and Peri (2005) [30]. Following Mancusi, we include individual effects to account for individual heterogeneity and to allow for differences in the propensity to patent in each sector-country and an individual and time-varying error to account for the imperfect ability of patent counts to measure technological output. The incoming spillover pools from output and external sector-countries are just their respective knowledge stocks weighted appropriately as external knowledge does not flow perfectly to the input sector-country. Output spillovers can be defined as follows:

$$O_{ci,si,t} = \phi_{co,so} I_{co,so,t} \tag{3.1}$$

where $\phi_{co,so}$ is the weight and $I_{co,so,t}$ the knowledge stock of output sector so and country co. External spillovers that are from sector-countries different from the output sector-country can be defined as follows:

$$E_{ci,si,t} = \sum_{c_j} \sum_{s_j} \phi_{cj,sj} I_{cj,sj,t}, j \neq i, j \neq o \tag{3.2}$$

where the actual spillover pool is the weighted average of knowledge stocks in all sector-countries different from ci, si and co, so.[3] Following Peri (2005), we assume that citations are a noisy indicator of actual outflows $\phi_{ci,si,co,so,t}$ so that we need to account for input and output heterogeneity and the imperfect ability of citations to measure knowledge flows. We receive a function that depends on spillovers, input and output characteristics and an input-output error term:

$$\begin{aligned} C_{ci,si,so,co,t} = exp(\mathbf{xb} + \beta_1 lnI_{ci,si,t} + \beta_2 ln(\phi_{co,so} I_{co,so,t}) + \beta_3 ln(\sum_{c_j}\sum_{s_j}\phi_{cj,sj,}I_{cj,sj,t}) \\ + \sum_{c_i}\varphi_{c_i}D_{c_i} + \sum_{s_i}\varphi_{s_i}D_{s_i} + \sum_{c_o}\vartheta_{c_o}D_{c_o} + \sum_{s_o}\vartheta_{s_o}D_{s_o} \\ + \eta_{ci,si,t} + \eta_{co,so,t} + \epsilon_{ci,si,co,so,t}) \end{aligned} \tag{3.3}$$

The variables that have to be estimated based on this equation are described below. Essentially, $\mathbf{x}$ is a vector of gravity-like variables like geographical and technological characteristics of the cited and citing sector-country.

4 Data sources, variable definitions, and descriptive statistics

4.1 Data sources

The idea to use input-output tables to analyze knowledge flows goes back to Scherer (1984) [32] and has been elaborated on by Verspagen (1997, 1999) [36] [37]. Basically, a technology flow matrix measures how technological knowledge from one sector in a certain country spills over to other sectors in the same or other countries. Patent data comes from the European Patent Office (EPO) PATSTAT database (EPO, 2013) [7]. We use all published patents applied for all over the world between 1995 and 2005 that can be attributed to a technological field according to the International Patent Classification (IPC, WIPO, 2014) [38]. The number of forward citations is calculated for each year and for each "input" and "output" sector-country-pair. In order to avoid truncation of the forward citation counts, we consider 5-year-windows, i.e. forward citations that occur within 5 years after publication of the cited patent (see Squicciarini et al., 2013) [34].

Transformation of technological fields according to IPC subclasses to industries based on NACE codes is accomplished with concordance data from Lybbert and Zolas (2014) [19].

We first matched the patent data with country data from World Development Indicators (The World Bank, 2014) [3]. Then, we matched the resulting dataset with several other datasets from OECD at industry level (ANBERD and STAN database). We ended up with 22 countries that could be used in our estimations. Finally, geographical distance measures between countries from the Centre d'Etudes Prospectives et d'Informations Internationales were attached (CEPII, 2011) [24].

[3] Please note that input and output sector-countries can be similar. However, to qualify as sector-country that is external to the input-output pair either the country or the sector have to be different.

4.2 Variable definition

4.2.1 Absorptive capacity and spillovers

We construct variables for absorptive capacity for each sector-country and spillovers across sector-countries. R&D stocks are calculated based on the inventory perpetual method as described in Hall et al. (2010) [11]. We use 15% as depreciation rate. For absorptive capacity, we simply use the one-year lag of the R&D stock that can be accrued to the focal sector and country. If there are spillovers from the output sector-country or from other regions and countries, they need to be weighted appropriately as we cannot assume that external knowledge can be absorbed perfectly. We follow Mancusi (2008) and apply the share of backward citations of sector-country cj, sj that accrues to a specific sector-country ci, si in total backward citations as weighting scheme. $\phi_{cj,sj}$ is calculated as relative citations from patent applications in sector-country ci, si to patent applications in cj, sj. The intuition is that the more sector-country cj, sj gets cited by ci, si, the more it is likely that its knowledge diffuses to ci, si (Hall et al., 2010, p. 1068). Backward citation links are noisy but common indicators of incoming knowledge from other sectors/countries. The assignment of backward citations to sectors and countries works in the same way as for outgoing knowledge as measured with forward citations.

4.2.2 Technological distance

Following Peri (2005) [30], Jaffe (1986) [13] and Maurseth and Verspagen (2002) [23], we are also trying to capture technological distance between sectors and countries based on the share of patents that these sectors and countries have in different technological fields (IPC) and on differences in R&D spending per employee and sector-country. The first measure captures differences in technological specialisation between two countries and is defined as follows:

$$TECHDIST_{ci,co} = 1 - SPECCORR_{ci,co} \tag{4.1}$$

where $SPECCORR_{ci,co}$ is the uncentered correlation coefficient between the share of patents of ci and co in the 17 industries considered here. A value close to 1 indicates a large degree of sectoral specialization.

We essentially expand the existing measure by also including a sectoral dimension, i.e. by measuring whether two sectors are technologically close in specialization. The inclusion of sectoral distances is involved as both the sectoral assignment of patents and the distance measures are based on IPC classes. Therefore, we look at each sector separately (the patents were assigned to sectors based on the IPC-industry concordance beforehand), assign all IPC classes that occur in patent applications assigned to a specific sector (not only IPC classes that occur in the respective sector definition). Based on this assignment, we calculated distance measures for sector-countries separately for each sector-country. The specialization index becomes $TECHDIST_{ci,si,co,so} = 1 - SPECCORR_{ci,si,co,so}$, where the correlation is measured between the share of patents of ci, si and co, so in the IPC classes occurring in the underlying patent applications.

4.2.3 Further variables

The basic specification of a gravity model in the trade literature includes supply factors of the export country, demand factors of the import country, and trade supporting and impeding determinants (geographical and cultural proximity) (Egger and Pfaffermayr, 2003) [6]. We use the natural logarithm of distance in kilometers between the most populated cities of two countries, denoted by *lndist*, a binary variable measuring if two countries share a land common border, *contig*, and a binary variable, *language*, whether two countries share a common official language as cultural and geographic variables. Finally, we include a binary variable measuring whether former colonial relationships between two countries existed, *colony* (for detailed description of these variables, see table 1). Following the trade literature, we include both the natural logarithm of GDP and the natural logarithm of GDP per capita as measures of market size and the quality of the economic and institutional environment of a country. Furthermore, we include the number of researchers in R&D per Mio. of people as proxy for a country's human capital. At industry level, we include variables measuring R&D intensity and investment intensity (R&D expenditures and investments as a share of value added) and the natural logarithm of the number of employees as a measure of the size of the industry.

4.3 Descriptive statistics

Table 2 shows the summary statistics for the main variables we use in the estimations and the sample that is used in the estimations. The distributions of patent applications and especially of forward citations are very skew.

Table 3 shows summary statistics for some key variables divided into industries and countries. The industries are summarized into a high-tech and low-tech sector based on a OECD definition that relies on R&D intensities (see OECD, 1997) [12][4]. The high-tech industries are indeed the industries with the highest values for the R&D stock. They are also the sectors with above-average number of patents and forward citations.

5 Estimation strategy

For estimation, we use count data models for the number of forward citations that occur between input and output sector-countries. We estimate both a pooled Poisson model and a fixed effects (FE) Poisson model. In the first case, we use the Poisson pseudo-maximum-likelihood (PPML) estimator by Santos Silva and Tenreyro (2006) [33].

[4]The same classification will be used later on in the estimations for high-tech and low-tech sectors.

6 Estimation results

6.1 Basic results

6.1.1 Input R&D stock and output and external R&D spillovers

The basic results for sector-country pairs where the number of forward citations is positive can be found in table 4 [5]. In column (1) to (6), the (weighted) R&D stocks are inserted separately. The coefficient for the weighted R&D stock from both the output and external sector-countries is highly significant and positive in both the pooled model and the FE specification, thus suggesting significant spillover effects from these sector-countries on further input output knowledge diffusion. The coefficients retain their signs and significance if added jointly (columns (7) to (8)). The internal R&D stock's coefficient, however, is not significant in the FE model. Our measures of technological distance display significantly negative coefficients in all specifications as expected. Hypotheses 1b and 2 cannot be rejected. Hypothesis 1a receives support only partly.

Spillovers from the output sector-country to the input sector-country makes it more likely that knowledge flows to the output sector-country in the future. Our interpretation of these results is that there must be strong knowledge exchange and linkages between input-output sector-countries. First, the input sector-country uses these spillovers in addition to own accumulated knowledge in order to develop new patented inventions that can only built on by a technologically close sector-country, namely the output sector-country. Second, the output sector-country also accumulates further tacit knowledge by citing these inventions which increases the likelihood that citations occur between these technologically close sector-countries.

Our results show that sector-countries that are close in technological space cite each other over time and that spillovers and subsequent knowledge flows thus should mainly take place between these sector-countries. Spillovers from the subsequently citing sector-countries increase knowledge flows back to the same sector-country. We also find evidence that interindustry spillovers matter, not only for sector-countries that are in an input-output relationship.

6.1.2 External high-tech and low-tech R&D spillovers

In column (11) and (12), we account for the fact that external sector-countries are heterogenous so that it might be difficult to capture external spillover effects with just one variable. Indeed, once we separate the external weighted R&D stocks into a high-tech and low-tech component (i.e. R&D stocks pertaining to either external low-tech sectors or high-tech sectors) , we get the result that only the high-tech stock displays a significant effect, thus supporting hypothesis 3.

6.2 Results for high-tech and low-tech sectors

6.2.1 Input R&D stock and output and external R&D spillovers

In table 5, we proceed by looking at knowledge flows occurring between high-tech and low-tech input and output sectors. [6] This analysis supplements the consideration of separate external high-

[5] The results for the whole sample are qualitativaly close although if there are not any citations

[6] We display results from FE estimations only.

tech and low-tech R&D stocks from above. Columns (1) and (2) refer to estimations where we restrict our sample to input high-tech and low-tech sectors, respectively. Columns (3) and (4) refer to output high-tech and low-tech sectors. Results for (1) and (2) indicate that output and external spillovers are important for knowledge diffusion from both high-tech and low-tech sectors. For the low-tech input sectors, we get a negative coefficient for internal R&D stock, indicating that internal low-tech knowledge creates a barrier for further knowledge diffusion. From pooled regressions, we can see that for low-tech sectors, geographic distance is much more important, indicating that high-tech knowledge flows across borders more easily. For further knowledge diffusion from high-tech sectors to other high-tech sectors, output and external spillovers still play a significant role as can be seen from column (5), but for low-tech input output pairs as in (6) only external spillovers play a role. For (5), technological distance between countries matter, but for (6) only sectoral technological distance play a role. High-tech sectors might draw on other sectors' knowledge more easily than low-tech sectors which might refer to a higher absorptive capacity.

Finally, we look at knowledge flows between high-tech and low-tech sectors, i.e. input output pairs where the input sector is high-tech and the output sector low-tech or conversely (columns (7) and (8)). The internal R&D stock of high-tech input sectors and external spillovers display highly significant and positive coefficients. In contrast, for low-tech input sectors, only the knowledge stemming from the high-tech output sector plays a role for further knowledge flows between these sectors. These results indicate that low-tech sectors' knowledge diffusion mainly hinges on high-tech knowledge generated in certain sectors and that knowledge generated in these sectors is the main driver of further knowledge diffusion. In contrast, knowledge stemming from low-tech sectors is not used purposefully by other sectors for further knowledge exchange. It can even create an impediment for further knowledge flows if both sectors are low-tech. The results are perfectly in line with what we stated in hypotheses 4a and 4b. They underline the argument on absorptive capacity and catching-up of laggards that other authors formulated for countries and the effect on total factor productivity. Obviously, sector-countries lagging behind the technological frontier not only catch up by learning from more advanced sector-countries, they also create further potential of knowledge diffusion by drawing on advanced knowledge. In contrast, high-tech sectors are are a source of knowledge rather than enablers of further knowledge exchange between input output pairs.

6.2.2 External high-tech and low-tech R&D spillovers

In table 6, we go into further detail by accounting for high-tech and low-tech external R&D spillovers as already did in 6.1.2 for all sector-country pairs. External high-tech spillovers display significant and positive coefficients for all high-tech-low-tech pairs unless the input sectors are low-tech and the output sectors are high-tech (column (8)). Knowledge diffusion into low-tech sectors based on high-tech sectors' knowledge, in turn, benefits both from low-tech and high-tech external knowledge (7). Low-tech external spillovers are not found to play a role if both the input and the output sectors are low-tech (6). Low-tech sectors seem to be "picky" and search exclusively for high-tech knowledge that spills either from the output sector or from external sources. In addition, it seems to be more convenient to draw on knowledge that comes from sectors where an input-output relationship exists, in contrast to external sectors. Hypothesis 5 was formulated ambiguously with respect to the effect of external high-tech spillovers for knowledge diffusion that is based on either high-tech or low-tech sectors. Our results indicate that external high-tech spillovers are relevant for all kind of sector pairs except for the case that the input sectors are low-tech and the output sectors are high-tech. In this case, further knowledge diffusion is enabled by high-tech spillovers stemming from the output sector directly.

6.3 Results for different industries

6.3.1 Input R&D stock and output and external R&D spillovers

In this section, we gather further insights into industry specificities with respect to knowledge acquisition and diffusion. To this end, we run the estimations for each input sector separately. Table 7 shows the results from the FE models. Some industries are ”introverted” and do not search for external knowledge outside the input output relationship. Most notably, for most of the high-tech industries external knowledge acquisition is limited to the output sector or do not play a role at all. For the Chemical and Transport industry, the respective coefficient of external spillovers is negative but insignificant. The Electrical industry only draws on knowledge generated in the output sector, but is not sourcing further external knowledge. In sum, the results support the results from above that low-tech sectors are more open to external knowledge acquisition and knowledge from the output sector as they can draw a larger benefit from this knowledge. High-tech sectors, in turn, are a source rather than receivers of external knowledge. In some high-tech sectors, the process of knowledge acquisiton and generation seems to be completely isolated from external sector-countries.

6.3.2 External high-tech and low-tech R&D spillovers

In this section, we again distinguish between external high-tech and low-tech R&D spillovers. For almost all industries where external knowledge spillovers matter for diffusion, only the spillovers from external high-tech sectors have an impact (see table 8). For a couple of industries where the coefficients of the high-tech R&D stocks are especially large, the low-tech R&D coefficient is even significantly negative. This result shows that the respective sectors can only enhance further knowledge diffusion if they absorb high-tech knowledge. If they absorbed more low-tech knowledge, further diffusion would get stuck. We also get the somehow interesting result that diffusion in the Electrical industry only benefits from knowledge spilling from low-tech sectors. Machinery is again at odds with other high-tech industries as both internal R&D and external high-tech R&D have significantly positive coefficients, whereas external knowledge spillovers do not matter for any other high-tech industry.

6.4 Robustness and further findings

We provide three additional robustness checks. First, we check whether the results are driven by sector-country pairs that consist of the same input and output sector, country or both although we already control for these pairs with dummies in the pooled regressions. In sum, the basic results are not affected from sector-countries being the same or not.

Second, we check whether the inclusion of ”patent scope” and ”number of claims” change our results.[7] The patent scope is the technological breadth of a patent measured by the number of technological fields that a patent comprises. The number of claims refer to the legal claims that a

[7] Results are not shown.

patent makes. Both indicators are associated with value and quality of a patent (see Squicciarini et al., 2013 [34]). Hence, they might be drivers of forward citations. We check whether the inclusion of industry averages makes other results obsolete. Although their coefficients are highly significant, the other results are not affected at all.

Third, we check how our results change if we use another definition of "high-tech" industries. Our hypotheses were formulated with respect to a so-called "technological frontier" and we presumed that high-tech sectors are closer to this frontier. However, as our sectors are defined relatively broadly, they might still contain very heterogeneous firms in terms of technological advancement. Moreover, we did not distinguish which countries are at the top. Therefore, we repeat the analysis from above 6.2 where we conditioned on high-tec or low-tech input and output sectors, now only defining sector-countries with R&D intensity higher or equal the 99% quantile as high-tech. Now, top high-tech sectors are restricted to "Electrical and Optical Equipment" and "Transport Equipment" and comprise only a few "frontier" countries (and not all countries that have patents in a certain high-tech sector as in the more general definition). Results are shown in table 9. Compared to table 5, the results are different, but it should be noted that we take into account two high-tech industries and a few high-tech countries that generate the frontier. Instead, the results confirm main insights from table 7 where we looked at different industries. First, top high-tech sector-countries' knowledge diffusion does not benefit from further external knowledge, whereas low-tech sectors' does. Second, technological distance does not play any role if top high-tech sector-countries are involved. New insights are, third, that low-tech sectors were found to draw on high-tech knowledge, but not on top high-tech knowledge generated by the few sector-countries that are outstanding with respect to R&D intensity (column (8)), and fourth, that top high-tech sector-countries draw on knowledge from the output low-tech sector-country (column (7)), whereas for the more general high-tech definition, high-tech sectors avoid drawing on low-tech knowledge and search for external knowledge. The latter result might be due to the larger knowledge base outside the input-output relationship when using the more restrictive definition.

7 Conclusions

In this paper, we looked at international and inter-sectoral knowledge flows between sector-countries as measured with patent citations. In contrast to previous studies, we used a much more detailed dataset that goes down to the sector-country input output level. New elements in this study are that we analyzed the effect of knowledge spillovers coming from internal and external sources on further knowledge diffusion between a sector-country pair, that we considered technological distance at both the sectoral and country level, and that we provided a detailed analysis for high-tech sectors. Our results show that technological distance and spillovers from output and external sector-countries are very important in explaining further knowledge flows between input and output sector-countries. In particular, our distinction between sectoral and cross-country technological distance seems to be important at this level of analysis as both measures add own explanatory power but behave differently in some specifications. Knowledge exchange between input-output sectors seems to be a self-sustaining process, but external knowledge can also play an important role in this process. The analysis for industries and high-tech sectors makes clear that there is considerable heterogeneity across industries so that the full sample analysis may hide important industry specificities. In fact, estimating the models for different input and output sectors separately shows that the use of external knowledge varies across sectors. Econometric methods are necessary to understand the knowledge absorption in input-output relationships that could be easily misinterpreted when looking at descriptive statistics where the largest patentees also appear to be the largest sources and receivers of knowledge. Our main results from this part of the analysis are the following: First, a low-tech sector's diffusion mainly depends on incoming knowledge from high-tech sectors whereas a high-tech sector's diffusion solely depends on knowledge generated in the output sector where the own knowledge goes to later on. Second, high-tech sectors' innovations process seem to take place more in isolation, whereas low-tech sectors actively search for high-tech knowledge. Third, high-tech knowledge is generally used as a source and thus more attractive for the innovation process than low-tech knowledge.

Given the attractiveness of high-tech knowledge compared to low-tech knowledge, for the sequential innovation process it might be important that knowledge diffuses to low-tech sectors. Otherwise, bottlenecks might arise so that low-tech sectors do not invest enough in own R&D. From a policy point of view, it is interesting to evaluate whether sectors can access high-tech knowledge of high-tech sectors to a sufficient degree. When the innovation process is rather isolated, exchange between sectors and countries might not be sufficient to sustain knowledge flows that are important for sequential inventions. In this context, the finding that the knowledge flows from top high-tech sectors like "Electrical and Optical Equipment" only depend on knowledge from the output sector but not on other external knowledge is particularly striking. Obviously, these sectors need highly specialized knowledge that can be only provided by sectors with that links are already established. For the top R&D performers, sectoral technological distance is not found to play a role so that knowledge can flow smoothly at least between input and output sector. However, one might ask whether sequential innovation performance in these sectors could benefit from more knowledge exchange with external sectors and how one could enable external low-tech sectors to adopt and use knowledge from the technological edge.

The major limitation of this study lies in the fact that we use patent citations as proxy of knowledge flows. Although this is a common measure used in literature, the well-known limitations of patent data apply. Future research should try to collect further international and inter-sectoral data that is able to capture knowledge flows and repeat the analysis. Unfortunately, data embodying knowledge exchange among humans, e.g. labor turnover or immigration of high potentials, is only available for very limited contexts. Indeed, at sector-country level it is very hard to find appropriate data aside from patents that is available for a significant number of sector-countries. A further limitation is that we are only able to trace a very small part of the sequential innovation process although the time series would allow to take into account the sequentiality and complexities of knowledge diffusion and innovation processes. Although our study is able to disclose some of the complex relationships, further work and more advanced methods are needed to fully understand the heterogeneity that is involved.

A Tables

Table 1: Description of variables

Variables	Description
fwcit5	Number of forward citations within 5 years after publication of patent applications in input sector-country si, ci by output sector-country so, co in year t
patents_si	Number of patent applications in si, ci, t
RD_i	R&D stock of si, ci, t
RD_bw_o	R&D stock of so, co, t weighted with relative backward citations from si, ci to so, co
RD_bw_osc	Weighted sum of R&D stocks of sj, cj, $(sj, cj) \neq (so, co), (sj, cj) \neq (si, ci)$, weighted with relative backward citations from si, ci to sj, cj
rdint	R&D intensity in si, ci, t and so, co, t
invint	Investment intensity in si, ci, t and so, co, t
lnempln	Natural logarithm of number of employees in si, ci, t and so, co, t
researcher	Researchers in R&D per Mio. people in ci, t and co, t
gdppc	GDP per capita in ci, t and co, t
lngdp	Natural logarithm of GDP in ci, t and co, t
techdist_c	Technological distance between ci, t and co, t (uncentered correlation coefficient between the share of patents of ci, t and co, t in the 17 industries in t)
techdist_s	Technological distance between ci, si, t and co, so, t (uncentered correlation coefficient between the share of patents of ci, si, t and co, so, t in the underlying technological fields in t)
lndist	Geographic distance between ci and co in natural logarithm
contiguity	Dummy for contiguity of ci and co
comlang_off	Dummy for common language of ci and co
colony	Dummy for former colonial relationship between ci and co
c_pair	Dummy indicating whether $ci = co$
s_pair	Dummy indicating whether $si = so$
cs_pair	Dummy indicating whether $ci = co$ and $si = so$

Table 2: Summary statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) p50	(6) max
fw_cit5	816,345	30.28	2,209.50	0.00	0.00	876,566.94
patent_count_si	816,345	4,907.77	16,457.93	0.78	689.78	261,053.11
lnRD_i	816,345	19.01	3.32	0.00	19.28	26.49
lnRD_bw_o	816,345	0.34	0.84	0.00	0.01	11.35
lnRD_bw_osc	816,345	4.98	2.49	0.00	5.22	11.37
techdist_c	816,345	0.11	0.09	0.00	0.09	0.47
techdist_s	816,345	0.74	0.23	0.00	0.82	1.00
rdint_i	816,345	2.79	5.08	0.00	0.93	48.35
rdint_o	816,345	2.79	5.08	0.00	0.93	48.35
invint_i	816,345	21.61	15.21	2.30	18.65	210.08
invint_o	816,345	21.61	15.21	2.30	18.65	210.08
lnempni	816,345	0.20	0.27	0.00	0.10	2.35
lnempno	816,345	0.20	0.27	0.00	0.10	2.35
lngdp_i	816,345	12.69	1.50	9.54	12.62	16.39
lngdp_o	816,345	12.69	1.50	9.54	12.62	16.39
lngdppc_i	816,345	9.74	0.64	8.31	9.98	10.79
lngdppc_o	816,345	9.74	0.64	8.31	9.98	10.79
researchers_i	816,345	0.26	0.13	0.10	0.24	0.80
researchers_o	816,345	0.26	0.13	0.10	0.24	0.80
lndist	816,345	7.34	1.18	3.98	7.28	9.81

Table 3: Summary statistics per sector and country: Number of forward citations, number of patents, R&D stock in natural logarithm

	fwcit5		patents_si		lnRD_i	
si	Mean	Sd	Mean	Sd	Mean	Sd
Low-tech sectors						
Agriculture, Hunting, Forestry and Fishing	12.2	157.8	3,637.5	6,571.7	17.4	3.3
Mining and Quarrying	12.0	139.4	3,693.6	7,310.1	16.2	5.3
Food, Beverages and Tobacco	17.7	491.3	3,711.3	7,896.5	19.4	2.0
Textiles and Leather Products	15.3	154.5	5,657.1	9,437.8	18.6	1.4
Wood and Products of Wood and Cork	1.4	20.8	573.4	957.0	16.5	3.1
Pulp, Paper, Printing and Publishing	17.8	459.5	2,868.2	5,678.9	18.3	2.4
Coke, Refined Petroleum and Nuclear Fuel	6.3	142.7	1,167.2	2,229.2	18.9	3.1
Rubber and Plastics	5.3	87.5	1,121.4	2,232.0	19.5	1.6
Other Non-Metallic Mineral	8.3	136.1	1,650.1	2,956.8	18.6	2.2
Basic Metals and Fabricated Metal	40.9	902.8	6,628.9	13,129.1	19.9	1.7
Machinery, nec	45.8	1,068.2	8,734.4	17,446.4	20.6	1.9
Electricity, Gas and Water Supply	7.1	110.7	1,551.6	2,854.3	17.4	4.9
Construction	14.0	221.8	3,725.6	6,145.3	18.2	2.3
High-tech sectors						
Chemicals and Chemical Products	66.8	1,589.2	12,808.2	29,653.9	21.5	1.9
Electrical and Optical Equipment	199.8	8,561.0	19,206.1	47,261.7	21.9	2.1
Transport Equipment	19.0	351.3	3,659.2	7,102.2	21.0	2.7
Manufacturing, Nec; Recycling	4.1	76.8	985.0	1,941.9	17.3	4.6
Total	30.3	2,209.5	4,907.8	16,457.9	19.0	3.3
	fwcit5		patents_ci		lnRD_i	
ci	Mean	Sd	Mean	Sd	Mean	Sd
AT	3.1	21.7	10,494.6	561.9	19.1	1.6
AU	1.5	6.5	8,247.8	2,100.6	19.3	0.5
BE	4.3	39.7	8,088.1	1,020.2	19.6	1.6
CA	17.5	389.6	21,174.3	3,867.6	20.4	1.3
CZ	0.2	1.5	2,426.9	168.2	18.2	1.8
DE	80.2	615.8	187,724.8	16,537.5	21.5	1.8
EE	0.0	0.2	142.0	0.0	15.5	1.4
ES	1.8	14.9	13,577.0	1,383.9	19.9	1.3
FI	3.2	27.7	16,108.6	1,309.5	18.8	1.3
FR	21.2	217.6	69,909.5	5,303.7	21.4	1.6
GB	20.8	273.3	47,951.5	3,109.4	21.5	1.6
GR	0.1	0.9	343.8	37.8	17.3	1.0
HU	0.2	2.8	2,380.1	273.8	16.6	2.9
IE	1.2	18.1	2,651.9	355.1	17.6	2.2
IT	5.9	46.7	25,433.5	2,006.5	19.7	3.2
KR	27.8	583.4	101,531.2	50,083.2	20.6	1.8
NL	14.3	175.9	29,655.7	6,578.2	19.7	1.6
PL	0.2	2.6	5,174.0	544.8	18.6	1.2
PT	0.1	0.9	516.9	114.0	17.4	1.2
SI	0.1	0.9	596.0	143.6	15.9	3.4
SK	0.1	0.8	426.2	45.9	12.3	8.0
US	490.9	11,057.8	406,065.5	60,325.1	23.3	1.8
Total	30.3	2,209.5	45,547.7	88,706.3	19.0	3.3

Table 4: Poisson models, dependent variable: number of forward citations that input sector-country receives from output sector-country

VARIABLES	(1) Pooled Poisson	(2) Poisson FE	(3) Pooled Poisson	(4) Poisson FE	(5) Pooled Poisson	(6) Poisson FE	(7) Pooled Poisson	(8) Poisson FE	(9) Pooled Poisson	(10) Poisson FE	(11) Pooled Poisson	(12) Poisson FE
l_lnRD_i	0.230***	0.108					0.155***	0.0842	0.137***	0.0336	0.139***	0.0430
	(0.0344)	(0.130)					(0.0316)	(0.127)	(0.0303)	(0.116)	(0.0294)	(0.100)
l_lnRD_bw_o			0.294***	0.0790***			0.282***	0.0779***	0.282***	0.0830***	0.282***	0.0852***
			(0.0441)	(0.0159)			(0.0433)	(0.0146)	(0.0425)	(0.0123)	(0.0441)	(0.0105)
l_lnRD_bw_osc					0.506***	1.877***			0.462***	1.891***		
					(0.0892)	(0.416)			(0.0764)	(0.407)		
l_lnRD_bw_hight											0.386***	1.780***
											(0.0677)	(0.342)
l_lnRD_bw_lowt											0.0170	0.0894
											(0.0417)	(0.279)
techdist_s	-3.209***	-1.287***	-2.553***	-1.299***	-3.248***	-1.284***	-2.572***	-1.389***	-2.610***	-1.274***	-2.601***	-1.271***
	(0.102)	(0.359)	(0.141)	(0.359)	(0.0968)	(0.339)	(0.142)	(0.332)	(0.136)	(0.337)	(0.134)	(0.338)
techdist_c	-4.223***	-3.285***	-3.658***	-3.056***	-4.232***	-2.418***	-3.677***	-3.081***	-3.622***	-2.187**	-3.634***	-2.184**
	(0.400)	(0.838)	(0.356)	(0.844)	(0.412)	(0.900)	(0.352)	(0.831)	(0.347)	(0.867)	(0.348)	(0.874)
rdint_i	0.0263***	0.00617	0.0267***	0.00768	0.0278***	0.00450	0.0235***	0.00676	0.0210***	0.00422	0.0213***	0.00427
	(0.00469)	(0.00749)	(0.00436)	(0.00753)	(0.00428)	(0.00746)	(0.00425)	(0.00741)	(0.00382)	(0.00730)	(0.00391)	(0.00728)
rdint_o	0.0246***	0.000176	0.0164***	9.95e-05	0.0266***	-0.000974	0.0168***	0.000680	0.0190***	0.000181	0.0187***	0.000548
	(0.00431)	(0.00821)	(0.00426)	(0.00793)	(0.00427)	(0.00805)	(0.00417)	(0.00800)	(0.00399)	(0.00794)	(0.00404)	(0.00783)
invint_i	0.00925**	0.00167	0.00625*	0.00126	0.00240	0.00151	0.00678*	0.00155	0.000787	0.00154	0.00147	0.00175
	(0.00386)	(0.00314)	(0.00370)	(0.00322)	(0.00461)	(0.00330)	(0.00351)	(0.00313)	(0.00384)	(0.00323)	(0.00391)	(0.00307)
invint_o	0.00812**	-0.00131	0.00745**	-0.00218	0.00751**	-0.00156	0.00759**	-0.00228	0.00699**	-0.00278	0.00707**	-0.00276
	(0.00364)	(0.00309)	(0.00321)	(0.00302)	(0.00373)	(0.00310)	(0.00306)	(0.00302)	(0.00299)	(0.00306)	(0.00301)	(0.00306)
lnempni	-0.120	-0.451	-0.0138	-0.422	0.0649	0.00342	-0.117	-0.436	-0.0932	0.0300	-0.0928	-0.0406
	(0.111)	(0.422)	(0.0956)	(0.423)	(0.113)	(0.435)	(0.0954)	(0.404)	(0.0939)	(0.409)	(0.0992)	(0.433)
lnempno	0.0610	-0.204	-0.166*	-0.274	0.0793	-0.178	-0.148	-0.278	-0.129	-0.257	-0.137	-0.302
	(0.109)	(0.460)	(0.0953)	(0.441)	(0.111)	(0.423)	(0.0929)	(0.434)	(0.0905)	(0.401)	(0.0945)	(0.386)
researchers_i	2.498***	2.607***	2.275***	2.655***	2.475***	1.969***	2.140***	2.531***	1.950***	1.815***	1.939***	1.685***
	(0.667)	(0.627)	(0.617)	(0.702)	(0.707)	(0.625)	(0.606)	(0.605)	(0.618)	(0.519)	(0.617)	(0.549)
researchers_o	2.395***	2.531***	3.560***	2.824***	2.334***	2.463***	3.519***	2.825***	3.479***	2.781***	3.468***	2.760***
	(0.541)	(0.609)	(0.558)	(0.630)	(0.576)	(0.561)	(0.546)	(0.608)	(0.553)	(0.530)	(0.542)	(0.479)
lngdppc_i	5.675***	6.251***	4.378***	5.970***	5.660***	6.267***	4.737***	6.027***	5.278***	6.101***	5.144***	5.907***
	(1.014)	(1.245)	(1.032)	(1.287)	(0.988)	(1.238)	(0.994)	(1.243)	(0.959)	(1.226)	(0.963)	(1.162)
lngdppc_o	3.310***	4.269***	6.099***	4.921***	3.209***	4.188***	6.047***	4.996***	6.059***	5.066***	6.039***	5.113***
	(1.083)	(1.338)	(1.067)	(1.270)	(1.060)	(1.307)	(1.051)	(1.278)	(1.027)	(1.268)	(1.019)	(1.306)
lngdp_i	-5.768***	-5.931***	-4.374***	-5.616***	-5.655***	-6.043***	-4.746***	-5.689***	-5.203***	-5.870***	-5.075***	-5.644***
	(0.935)	(1.195)	(0.968)	(1.219)	(0.915)	(1.167)	(0.939)	(1.196)	(0.921)	(1.174)	(0.924)	(1.129)
lngdp_o	-3.457***	-4.009***	-6.136***	-4.647***	-3.345***	-3.939***	-6.085***	-4.720***	-6.076***	-4.798***	-6.056***	-4.834***
	(0.970)	(1.267)	(1.007)	(1.210)	(0.950)	(1.247)	(0.996)	(1.218)	(0.982)	(1.216)	(0.968)	(1.251)
lndist	-0.0959***		-0.0406		-0.103***		-0.0419		-0.0466*		-0.0455	
	(0.0324)		(0.0289)		(0.0324)		(0.0282)		(0.0277)		(0.0279)	
contig	-0.125		-0.0712		-0.126		-0.0739		-0.0748		-0.0741	
	(0.0814)		(0.0796)		(0.0822)		(0.0778)		(0.0751)		(0.0763)	
comlang_off	0.255***		0.286***		0.268***		0.289***		0.300***		0.299***	
	(0.0775)		(0.0842)		(0.0791)		(0.0836)		(0.0830)		(0.0832)	
colony	0.0222		0.0217		0.0298		0.0206		0.0282		0.0278	
	(0.0697)		(0.0635)		(0.0697)		(0.0628)		(0.0608)		(0.0613)	
c_pair	1.324***		1.121***		1.321***		1.133***		1.141***		1.145***	
	(0.0799)		(0.0968)		(0.0808)		(0.0953)		(0.0933)		(0.0932)	
s_pair	0.0191		0.113*		0.00946		0.116*		0.112*		0.120*	
	(0.0752)		(0.0673)		(0.0743)		(0.0676)		(0.0643)		(0.0629)	
cs_pair	-0.164**		-0.173**		-0.236***		-0.181**		-0.258***		-0.282***	
	(0.0827)		(0.0706)		(0.0830)		(0.0705)		(0.0696)		(0.0871)	
Constant	43.74***		50.30***		10.77**		20.85***		20.79***		20.58***	
	(6.216)		(6.497)		(5.090)		(6.075)		(5.988)		(5.909)	
Observations	404,932	393,466	405,369	394,144	398,277	386,960	398,277	386,960	398,277	386,960	398,277	386,960
R-squared	0.929		0.935		0.932		0.938		0.942		0.942	
input sector dummies	YES		YES		YES		YES		YES		YES	
output sector dummies	YES		YES		YES		YES		YES		YES	
input country dummies	YES		YES		YES		YES		YES		YES	
output country dummies	YES		YES		YES		YES		YES		YES	
time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-130.8	-43.03	-130.4	-43.04	-130.1	-42.76	-129.7	-42.78	-129.6	-42.75	-129.6	-42.75
Number of id		67,017		67,183		66,206		66,206		66,206		66,206

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Poisson FE models for high-tech and low-tech sectors, dependent variable: number of forward citations that input sector-country receives from output sector-country

VARIABLES	(1) Input high-tech	(2) Input low-tech	(3) Output high-tech	(4) Output low-tech	(5) Input high-tech & output high-tech	(6) Input low-tech & output low-tech	(7) Input high-tech & output low-tech	(8) Input low-tech & output high-tech
l_lnRD_i	0.217	-0.140**	0.0179	0.0414	0.200	-0.121*	0.501***	-0.153
	(0.308)	(0.0623)	(0.175)	(0.0654)	(0.358)	(0.0650)	(0.173)	(0.101)
l_lnRD_bw_o	0.0644***	0.135***	0.0809***	0.0267	0.0638***	0.0714	-0.0271	0.145***
	(0.0138)	(0.0210)	(0.0150)	(0.0457)	(0.0160)	(0.0459)	(0.0736)	(0.0241)
l_lnRD_bw_osc	1.881***	1.453*	1.478***	3.046***	1.788***	3.087***	2.678***	0.0483
	(0.512)	(0.753)	(0.552)	(0.447)	(0.600)	(0.322)	(0.742)	(1.252)
techdist_s	-1.178**	-1.438***	-1.310**	-1.315***	-1.509	-1.413***	-1.179**	-1.385***
	(0.597)	(0.246)	(0.555)	(0.327)	(0.998)	(0.285)	(0.557)	(0.365)
techdist_c	-3.019**	-0.529	-3.021**	-0.967**	-3.620**	-0.569	-1.402**	-0.705
	(1.226)	(0.507)	(1.302)	(0.394)	(1.552)	(0.432)	(0.708)	(1.023)
rdint_i	0.00176	0.103***	0.00758	-0.00590	0.00531	0.0902***	-0.0151	0.111***
	(0.00820)	(0.0218)	(0.00789)	(0.00970)	(0.00840)	(0.0281)	(0.0125)	(0.0328)
rdint_o	-0.00412	0.00351	3.52e-05	0.0977***	-0.00471	0.0633**	0.117**	0.00417
	(0.00746)	(0.0125)	(0.00891)	(0.0332)	(0.00776)	(0.0277)	(0.0587)	(0.0140)
invint_i	0.00825*	-0.00132	0.00152	0.00377	0.00901	3.76e-05	0.0115**	-0.00262
	(0.00471)	(0.00190)	(0.00416)	(0.00271)	(0.00631)	(0.00240)	(0.00568)	(0.00316)
invint_o	-0.00240	-0.00244	0.000360	-0.00238	-7.60e-05	-0.00282	-0.00128	-0.00207
	(0.00355)	(0.00364)	(0.00428)	(0.00161)	(0.00561)	(0.00211)	(0.00240)	(0.00605)
lnempni	-0.753	0.957***	-0.391	1.019***	-1.263*	1.119***	0.962	0.852*
	(0.701)	(0.348)	(0.502)	(0.377)	(0.762)	(0.425)	(0.778)	(0.449)
lnempno	-0.119	-0.118	-0.573	0.147	-0.194	0.180	0.122	-0.402
	(0.503)	(0.295)	(0.750)	(0.363)	(0.853)	(0.394)	(0.516)	(0.446)
researchers_i	1.575**	1.774***	1.934***	1.561***	1.749**	1.539***	0.771	1.789***
	(0.644)	(0.429)	(0.726)	(0.516)	(0.855)	(0.538)	(0.927)	(0.676)
researchers_o	2.576***	2.708***	3.282***	1.562***	3.227***	2.655***	0.329	2.534***
	(0.786)	(0.410)	(0.811)	(0.456)	(1.044)	(0.479)	(0.681)	(0.707)
lngdppc_i	8.311***	4.627***	7.370***	3.996***	10.08***	4.015***	3.373*	5.379***
	(2.301)	(0.742)	(1.761)	(0.831)	(2.807)	(0.876)	(1.889)	(1.072)
lngdppc_o	4.750**	5.374***	5.188**	5.350***	4.362	5.590***	4.894***	5.424***
	(1.848)	(0.773)	(2.555)	(0.748)	(3.109)	(0.877)	(1.120)	(1.403)
lngdp_i	-8.059***	-4.275***	-7.127***	-3.859***	-9.820***	-3.870***	-3.305*	-4.801***
	(2.183)	(0.766)	(1.678)	(0.806)	(2.655)	(0.869)	(1.807)	(1.121)
lngdp_o	-4.549***	-4.990***	-4.995**	-4.885***	-4.343	-5.402***	-4.132***	-4.858***
	(1.764)	(0.732)	(2.403)	(0.766)	(2.900)	(0.860)	(1.148)	(1.336)
Observations	101,961	284,999	102,029	284,931	28,113	211,083	73,848	73,916
Number of id	16,963	49,243	17,020	49,186	4,494	36,717	12,469	12,526
time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-27.50	-15.21	-27.90	-14.83	-20.29	-7.638	-7.182	-7.561

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Poisson FE models for high-tech and low-tech sectors with external high-tech and low-tech R&D stocks, dependent variable: number of forward citations that input sector-country receives from output sector-country

VARIABLES	(1) Input high-tech	(2) Input low-tech	(3) Output high-tech	(4) Output low-tech	(5) Input high-tech & output high-tech	(6) Input low-tech & output low-tech	(7) Input high-tech & output low-tech	(8) Input low-tech & output high-tech
l_lnRD_i	0.179	-0.124**	0.0614	-0.0176	0.218	-0.100	0.280*	-0.118
	(0.281)	(0.0630)	(0.149)	(0.0668)	(0.327)	(0.0650)	(0.155)	(0.104)
l_lnRD_bw_o	0.0624***	0.137***	0.0888***	0.0226	0.0677***	0.0523	-0.0342	0.154***
	(0.0113)	(0.0219)	(0.0151)	(0.0454)	(0.0139)	(0.0496)	(0.0692)	(0.0261)
l_lnRD_bw_hight	1.634***	1.465**	1.484***	2.263***	1.638***	3.061***	1.290**	0.430
	(0.456)	(0.688)	(0.428)	(0.445)	(0.543)	(0.379)	(0.624)	(1.020)
l_lnRD_bw_lowt	0.199	0.00337	-0.0995	0.861**	0.0273	0.145	1.233***	-0.426
	(0.282)	(0.303)	(0.330)	(0.358)	(0.298)	(0.443)	(0.390)	(0.381)
techdist_s	-1.182**	-1.431***	-1.318**	-1.381***	-1.508	-1.387***	-1.378***	-1.396***
	(0.600)	(0.249)	(0.560)	(0.282)	(1.002)	(0.279)	(0.453)	(0.373)
techdist_c	-3.076**	-0.510	-3.015**	-0.858**	-3.647**	-0.531	-1.363*	-0.708
	(1.198)	(0.507)	(1.312)	(0.399)	(1.527)	(0.428)	(0.706)	(1.020)
rdint_i	0.00189	0.103***	0.00755	-0.00757	0.00550	0.0926***	-0.0167	0.111***
	(0.00816)	(0.0213)	(0.00768)	(0.00936)	(0.00834)	(0.0272)	(0.0125)	(0.0317)
rdint_o	-0.00332	0.00374	9.43e-05	0.101***	-0.00451	0.0626**	0.125**	0.00478
	(0.00765)	(0.0123)	(0.00883)	(0.0335)	(0.00785)	(0.0279)	(0.0589)	(0.0140)
invint_i	0.00837*	-0.00132	0.00181	0.00313	0.00950	0.000184	0.00617	-0.00279
	(0.00434)	(0.00191)	(0.00412)	(0.00249)	(0.00599)	(0.00238)	(0.00446)	(0.00315)
invint_o	-0.00227	-0.00244	0.000310	-0.00246	-2.26e-05	-0.00289	-0.00181	-0.00187
	(0.00348)	(0.00361)	(0.00442)	(0.00161)	(0.00558)	(0.00215)	(0.00245)	(0.00589)
lnempni	-0.802	0.917***	-0.484	1.208***	-1.372*	1.069**	1.657**	0.791*
	(0.735)	(0.352)	(0.516)	(0.387)	(0.779)	(0.432)	(0.832)	(0.458)
lnempno	-0.209	-0.142	-0.587	0.163	-0.237	0.193	0.172	-0.499
	(0.481)	(0.303)	(0.721)	(0.354)	(0.822)	(0.390)	(0.485)	(0.472)
researchers_i	1.510**	1.710***	1.786**	1.714***	1.609*	1.405**	1.460*	1.685***
	(0.697)	(0.431)	(0.769)	(0.538)	(0.926)	(0.564)	(0.869)	(0.646)
researchers_o	2.503***	2.663***	3.371***	1.608***	3.246***	2.541***	0.418	2.546***
	(0.719)	(0.408)	(0.729)	(0.465)	(0.959)	(0.494)	(0.695)	(0.703)
lngdppc_i	8.171***	4.450***	6.979***	4.441***	9.745***	3.796***	3.670*	4.951***
	(2.268)	(0.791)	(1.749)	(0.922)	(2.824)	(0.928)	(1.909)	(1.164)
lngdppc_o	4.800**	5.371***	5.332**	5.368***	4.478	5.519***	4.863***	5.628***
	(1.866)	(0.777)	(2.623)	(0.722)	(3.146)	(0.852)	(1.028)	(1.458)
lngdp_i	-7.886***	-4.095***	-6.689***	-4.355***	-9.443***	-3.657***	-3.725**	-4.354***
	(2.162)	(0.835)	(1.694)	(0.923)	(2.689)	(0.975)	(1.852)	(1.207)
lngdp_o	-4.577**	-4.979***	-5.142**	-4.911***	-4.454	-5.335***	-4.118***	-5.041***
	(1.782)	(0.736)	(2.470)	(0.734)	(2.938)	(0.843)	(1.052)	(1.392)
Observations	101,961	284,999	102,029	284,931	28,113	211,083	73,848	73,916
Number of id	16,963	49,243	17,020	49,186	4,494	36,717	12,469	12,526
time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-27.50	-15.21	-27.90	-14.83	-20.29	-7.637	-7.180	-7.560

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Poisson FE models for different industries, dependent variable: number of forward citations that input sector-country receives from output sector-country

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
l_lnRD_i	-0.127	-0.205**	2.595*	0.144	-0.247***	0.806***	-0.119	0.584	0.728***
	(0.166)	(0.0971)	(1.365)	(0.106)	(0.0942)	(0.178)	(0.160)	(0.419)	(0.216)
l_lnRD_bw_o	0.0929**	0.206***	0.126**	0.155***	0.306**	0.241**	0.0603***	0.0431	0.0939**
	(0.0399)	(0.0381)	(0.0621)	(0.0384)	(0.141)	(0.101)	(0.0227)	(0.0290)	(0.0378)
l_lnRD_bw_osc	0.599	1.801**	-2.204	2.676***	3.392***	1.434**	1.317***	-0.357	0.254
	(0.748)	(0.827)	(2.098)	(0.364)	(0.941)	(0.612)	(0.469)	(1.103)	(0.318)
techdist_s	-0.181	-1.964***	-1.117	-1.653***	-0.0167	-0.838	-0.965	-1.038*	-0.448
	(0.895)	(0.563)	(1.127)	(0.447)	(0.364)	(0.529)	(0.658)	(0.587)	(0.589)
techdist_c	0.842	-1.622*	-4.951***	0.460	-1.082	-0.506	-3.476***	-2.011***	-0.445
	(1.200)	(0.863)	(1.485)	(0.824)	(1.217)	(1.363)	(0.956)	(0.775)	(0.825)
rdint_i	0.449***	0.196***	-0.376	0.0301	0.0114	-0.282***	-0.0163	-0.0432***	0.0267
	(0.167)	(0.0466)	(0.372)	(0.0441)	(0.0933)	(0.0587)	(0.0187)	(0.0114)	(0.0313)
rdint_o	-0.00706	-0.0221	0.0466**	0.00690	-0.00668	-0.00481	-0.00692	0.00486	0.00326
	(0.0138)	(0.0165)	(0.0189)	(0.0116)	(0.00429)	(0.0103)	(0.00737)	(0.00502)	(0.00604)
invint_i	0.00128	-0.000894	0.00268	0.0206**	0.0262***	-0.0350***	-0.000989	-0.0122*	0.0165***
	(0.0122)	(0.00292)	(0.0119)	(0.00970)	(0.00456)	(0.0123)	(0.000868)	(0.00624)	(0.00613)
invint_o	0.00157	0.00170	0.00952	-0.00202	-0.00448	-0.00438	0.00649*	0.00425*	0.00397
	(0.00378)	(0.00298)	(0.0108)	(0.00330)	(0.00463)	(0.00733)	(0.00336)	(0.00256)	(0.00282)
lnempni	-5.396***	2.613	0.707	-3.966***	1.864	2.481**	-2.149	0.451	-0.354
	(1.092)	(3.991)	(3.079)	(0.956)	(2.001)	(1.090)	(5.784)	(2.625)	(0.723)
lnempno	1.817***	1.141	-0.159	-0.0178	-0.214	1.914***	0.266	-0.0225	0.235
	(0.557)	(0.735)	(1.076)	(0.482)	(0.420)	(0.508)	(1.226)	(0.779)	(0.418)
researchers_i	-2.859**	0.867	-1.934	-0.530	1.769*	0.243	2.488***	-2.452***	1.690***
	(1.169)	(0.963)	(2.016)	(0.697)	(1.021)	(1.002)	(0.753)	(0.808)	(0.564)
researchers_o	0.330	1.232	2.101	2.025***	1.907*	-0.714	0.720	1.049	3.100***
	(1.420)	(0.950)	(1.790)	(0.628)	(0.974)	(0.824)	(0.577)	(0.775)	(0.562)
lngdppc_i	-9.945***	-10.98***	-3.126	-7.852***	0.127	8.008***	6.628***	-0.907	3.636***
	(2.734)	(3.271)	(4.937)	(2.542)	(2.232)	(1.836)	(2.133)	(1.716)	(1.405)
lngdppc_o	6.744***	2.196	5.102	5.295***	5.511***	0.738	6.144***	4.849***	6.956***
	(1.920)	(2.057)	(3.350)	(1.206)	(1.648)	(1.918)	(2.151)	(1.496)	(1.500)
lngdp_i	9.076***	10.25***	2.010	7.368***	0.0972	-6.388***	-6.302***	0.770	-3.340**
	(2.522)	(3.316)	(4.655)	(2.343)	(2.177)	(1.994)	(2.174)	(1.656)	(1.408)
lngdp_o	-6.365***	-0.904	-5.392*	-4.534***	-5.184***	-0.282	-5.811***	-4.188***	-6.665***
	(1.635)	(2.065)	(2.792)	(1.217)	(1.649)	(1.903)	(2.155)	(1.467)	(1.498)
Observations	15,845	18,041	24,705	24,847	18,526	21,833	14,833	25,405	19,180
Number of id	2,807	2,961	4,249	3,876	3,533	3,636	2,802	4,616	3,575
time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-0.791	-0.846	-1.872	-1.507	-0.107	-1.391	-0.495	-6.019	-0.493

Cluster-robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The column numbers refer to the following industries:
(1) Agriculture, Hunting, Forestry and Fishing (2) Mining and Quarrying
(3) Food, Beverages and Tobacco (4) Textiles and Leather Products
(5) Wood and Products of Wood and Cork (6) Pulp, Paper, Printing and Publishing
(7) Coke, Refined Petroleum and Nuclear Fuel (8) Chemicals and Chemical Products
(9) Rubber and Plastics (10) Other Non-Metallic Mineral
(11) Basic Metals and Fabricated Metal (12) Machinery, nec
(13) Electrical and Optical Equipment (14) Transport Equipment
(15) Manufacturing, Nec; Recycling (16) Electricity, Gas and Water Supply
(17) Construction

VARIABLES	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
l_lnRD_i	1.478***	-0.285**	0.871***	0.462	-0.471	-0.195	-0.168***	-0.00429
	(0.341)	(0.139)	(0.190)	(0.519)	(0.426)	(0.173)	(0.0538)	(0.0661)
l_lnRD_bw_o	0.0835	0.0665*	0.0180	0.0442**	0.0155	0.154**	0.0331	0.0731**
	(0.0354)	(0.0245)	(0.0189)	(0.0498)	(0.0729)	(0.0488)	(0.0354)	
l_lnRD_bw_osc	1.404**	0.409	1.929***	0.788	-0.223	1.018	1.456***	2.761***
	(0.681)	(0.749)	(0.377)	(0.561)	(1.122)	(0.626)	(0.494)	(0.791)
techdist_s	-1.331**	-2.043***	-2.669***	0.151	0.718	-1.098	-3.454***	-1.023***
	(0.647)	(0.681)	(0.521)	(0.916)	(1.189)	(1.109)	(1.041)	(0.377)
techdist_c	-1.322	1.748**	-1.155	-4.039**	-0.431	0.469	0.137	-1.024*
	(0.867)	(0.879)	(0.847)	(1.693)	(1.347)	(1.221)	(0.794)	(0.607)
rdint_i	0.0560	0.198***	0.0858***	-0.00855	0.0147	0.0885	0.242***	-0.392**
	(0.0443)	(0.0623)	(0.0249)	(0.00834)	(0.0215)	(0.115)	(0.0648)	(0.185)
rdint_o	0.0237	-0.0220	-0.0336***	0.00354	-0.0395***	-0.0319*	-0.0122**	-0.00869
	(0.0191)	(0.0137)	(0.0117)	(0.00672)	(0.0123)	(0.0171)	(0.00499)	(0.0133)
invint_i	0.0233***	-0.0472***	0.00866	0.0178*	-0.0254**	0.0162	-0.00645*	-0.0492**
	(0.00452)	(0.00706)	(0.0140)	(0.00985)	(0.0117)	(0.0137)	(0.00351)	(0.0250)
invint_o	-0.00291	-0.0102*	0.00420	-0.00929	0.00564	-0.0175	-0.00402	0.00176
	(0.00557)	(0.00584)	(0.00539)	(0.00651)	(0.00656)	(0.0156)	(0.00467)	(0.00495)
lnempni	-1.755	0.648	0.228	-0.785	-2.152	2.755	6.271***	1.706**
	(2.823)	(0.645)	(0.902)	(1.281)	(1.716)	(2.337)	(2.196)	(0.809)
lnempno	-1.647	0.0616	0.127	0.799	-0.524	1.392	-0.896*	-1.050***
	(1.374)	(0.342)	(0.379)	(0.649)	(0.811)	(0.861)	(0.540)	(0.379)
researchers_i	3.107***	2.304***	2.224***	1.181	2.832**	1.331	3.649***	3.534***
	(0.857)	(0.609)	(0.566)	(1.350)	(1.360)	(0.993)	(0.622)	(0.881)
researchers_o	2.467***	4.147***	2.748***	2.127*	2.362***	4.698***	1.140*	2.273***
	(0.763)	(0.739)	(0.659)	(1.148)	(0.910)	(1.099)	(0.652)	(0.840)
lngdppc_i	3.744	4.236**	6.321***	13.99***	5.121*	3.049	-3.401**	6.317**
	(2.402)	(1.831)	(2.332)	(4.847)	(3.069)	(2.594)	(1.529)	(3.004)
lngdppc_o	5.464***	6.428***	5.658***	1.146	6.056***	5.752**	4.612**	5.172***
	(1.410)	(1.463)	(1.387)	(2.335)	(1.936)	(2.339)	(1.991)	(1.285)
lngdp_i	-4.042	-3.714**	-6.519***	-13.96***	-4.169	-3.029	3.166**	-7.047**
	(2.470)	(1.818)	(2.215)	(4.622)	(2.837)	(2.470)	(1.464)	(3.205)
lngdp_o	-4.805***	-6.029***	-5.630***	-1.235	-5.699***	-6.186**	-3.669*	-4.686***
	(1.310)	(1.445)	(1.336)	(2.161)	(1.867)	(2.422)	(1.952)	(1.278)
Observations	22,949	29,604	28,620	27,061	20,875	22,313	26,664	25,659
Number of id	4,192	4,644	4,836	4,102	3,409	3,947	4,431	4,590
time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-0.808	-4.158	-4.629	-14.71	-2.037	-0.416	-0.807	-1.431

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Poisson FE models for different industries with external high-tech and low-tech R&D stocks, dependent variable: number of forward citations that input sector-country receives from output sector-country

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
l_lnRD_i	-0.143	-0.213**	2.787**	0.125	-0.287***	0.845***	-0.106	0.641	0.665***
	(0.168)	(0.0978)	(1.380)	(0.0995)	(0.0967)	(0.164)	(0.168)	(0.423)	(0.209)
l_lnRD_bw_o	0.0897**	0.204***	0.0636	0.160***	0.281**	0.245**	0.0565**	0.0406	0.0997***
	(0.0390)	(0.0366)	(0.0776)	(0.0391)	(0.136)	(0.102)	(0.0250)	(0.0282)	(0.0378)
l_lnRD_bw_hight	-0.0325	1.319	-4.145	4.447***	4.898***	2.684***	0.973*	-0.814	1.454**
	(0.615)	(1.586)	(3.049)	(0.694)	(1.090)	(0.681)	(0.511)	(1.468)	(0.568)
l_lnRD_bw_lowt	0.990	0.679	4.429	-1.565**	-2.095*	-1.884***	0.609*	-0.163	-1.224***
	(0.725)	(0.995)	(2.734)	(0.635)	(1.074)	(0.328)	(0.340)	(0.194)	(0.412)
techdist_s	-0.237	-1.956***	-1.414	-1.626***	-0.0655	-1.011*	-0.985	-1.051*	-0.408
	(0.890)	(0.563)	(1.183)	(0.433)	(0.355)	(0.516)	(0.666)	(0.593)	(0.584)
techdist_c	0.992	-1.535*	-4.233***	0.522	-0.758	0.133	-3.463***	-2.066***	-0.653
	(1.204)	(0.818)	(1.350)	(0.808)	(1.224)	(1.386)	(0.956)	(0.765)	(0.848)
rdint_i	0.468***	0.195***	-0.438	0.00356	0.101	-0.203***	-0.0166	-0.0448***	0.0219
	(0.167)	(0.0475)	(0.380)	(0.0436)	(0.0927)	(0.0537)	(0.0181)	(0.0108)	(0.0316)
rdint_o	-0.00736	-0.0221	0.0435**	0.00720	-0.00712**	-0.00464	-0.00760	0.00450	0.00409
	(0.0139)	(0.0163)	(0.0175)	(0.0111)	(0.00407)	(0.0102)	(0.00717)	(0.00546)	(0.00549)
invint_i	0.00102	-0.000885	0.0136	-0.000286	0.0288***	-0.0413***	-0.00116	-0.0129*	0.0155***
	(0.0122)	(0.00314)	(0.0144)	(0.0103)	(0.00452)	(0.0119)	(0.000873)	(0.00732)	(0.00594)
invint_o	0.00157	0.00175	0.00951	-0.00128	-0.00625	-0.00650	0.00651*	0.00433*	0.00394
	(0.00379)	(0.00297)	(0.0106)	(0.00314)	(0.00479)	(0.00756)	(0.00337)	(0.00254)	(0.00277)
lnempni	-5.375***	2.602	-2.561	-1.115	3.220	2.448**	-1.550	0.246	-1.220
	(1.087)	(4.261)	(4.045)	(1.370)	(2.220)	(1.072)	(5.830)	(2.746)	(0.803)
lnempno	1.816***	1.131	-0.110	0.108	-0.238	1.950***	0.318	0.0307	0.238
	(0.559)	(0.720)	(1.099)	(0.479)	(0.415)	(0.514)	(1.220)	(0.741)	(0.423)
researchers_i	-3.002***	0.692	-3.684	-1.016	1.086	0.375	2.539***	-2.365**	1.493***
	(1.165)	(0.977)	(2.667)	(0.713)	(0.995)	(0.848)	(0.749)	(0.943)	(0.563)
researchers_o	0.345	1.213	2.037	1.943***	1.724*	-0.771	0.686	1.089	3.009***
	(1.418)	(0.945)	(1.816)	(0.650)	(0.939)	(0.752)	(0.570)	(0.784)	(0.551)
lngdppc_i	-8.825***	-10.59***	-3.721	-9.455***	-4.254	7.539***	6.792***	-1.012	2.870**
	(2.787)	(3.247)	(5.202)	(2.176)	(2.735)	(1.804)	(2.190)	(1.622)	(1.391)
lngdppc_o	6.769***	2.229	4.967	5.292***	5.638***	0.835	5.994***	4.832***	6.796***
	(1.921)	(2.061)	(3.286)	(1.204)	(1.616)	(1.879)	(2.162)	(1.558)	(1.498)
lngdp_i	8.008***	9.883***	2.574	8.721***	4.419*	-5.872***	-6.477***	0.889	-2.401*
	(2.612)	(3.288)	(4.857)	(2.003)	(2.622)	(1.979)	(2.232)	(1.499)	(1.394)
lngdp_o	-6.396***	-0.936	-5.297*	-4.524***	-5.319***	-0.324	-5.662***	-4.196***	-6.497***
	(1.637)	(2.069)	(2.767)	(1.215)	(1.623)	(1.854)	(2.171)	(1.535)	(1.495)
Observations	15,845	18,041	24,705	24,847	18,526	21,833	14,833	25,405	19,18
Number of id	2,807	2,961	4,249	3,876	3,533	3,636	2,802	4,616	3,575
time dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-0.791	-0.846	-1.869	-1.506	-0.107	-1.390	-0.495	-6.018	-0.493

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The column numbers refer to the following industries:
(1) Agriculture, Hunting, Forestry and Fishing (2) Mining and Quarrying
(3) Food, Beverages and Tobacco (4) Textiles and Leather Products
(5) Wood and Products of Wood and Cork (6) Pulp, Paper, Printing and Publishing
(7) Coke, Refined Petroleum and Nuclear Fuel (8) Chemicals and Chemical Products
(9) Rubber and Plastics (10) Other Non-Metallic Mineral
(11) Basic Metals and Fabricated Metal (12) Machinery, nec
(13) Electrical and Optical Equipment (14) Transport Equipment
(15) Manufacturing, Nec; Recycling (16) Electricity, Gas and Water Supply
(17) Construction

VARIABLES	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
l_lnRD_i	1.539***	-0.284**	0.903***	0.266	-0.365	-0.266	-0.169***	-0.00512
	(0.355)	(0.136)	(0.182)	(0.502)	(0.382)	(0.199)	(0.0540)	(0.0646)
l_lnRD_bw_o	0.0803	0.0655*	0.0346	0.0303	0.0567	0.165**	0.0304	0.0771**
	(0.0664)	(0.0342)	(0.0267)	(0.0204)	(0.0553)	(0.0767)	(0.0493)	(0.0370)
l_lnRD_bw_hight	0.563	0.188	2.372***	0.442	-0.155	2.008	1.059*	2.891***
	(0.764)	(1.043)	(0.507)	(0.526)	(1.184)	(1.328)	(0.633)	(1.112)
l_lnRD_bw_lowt	1.106***	0.286	-1.035*	0.621**	-0.502	-0.803	0.585	-0.121
	(0.364)	(0.724)	(0.595)	(0.309)	(0.384)	(0.977)	(0.640)	(0.630)
techdist_s	-1.347**	-2.051***	-2.763***	0.0739	0.485	-1.109	-3.470***	-1.080***
	(0.649)	(0.674)	(0.534)	(0.883)	(1.114)	(1.085)	(1.051)	(0.395)
techdist_c	-1.456*	1.729*	-0.957	-4.418***	-0.431	0.674	0.170	-1.006*
	(0.864)	(0.888)	(0.809)	(1.592)	(1.319)	(1.245)	(0.789)	(0.606)
rdint_i	0.0583	0.198***	0.0770***	-0.00885	0.0115	0.102	0.245***	-0.399**
	(0.0433)	(0.0621)	(0.0277)	(0.00854)	(0.0231)	(0.114)	(0.0659)	(0.184)
rdint_o	0.0240	-0.0221	-0.0327***	0.00817	-0.0370***	-0.0305*	-0.0122**	-0.00830
	(0.0190)	(0.0141)	(0.0118)	(0.00804)	(0.0112)	(0.0172)	(0.00500)	(0.0132)
invint_i	0.0256***	-0.0466***	0.00733	0.0174*	-0.0251**	0.00593	-0.00641*	-0.0468**
	(0.00500)	(0.00680)	(0.0139)	(0.00983)	(0.0114)	(0.0195)	(0.00375)	(0.0229)
invint_o	-0.00271	-0.0101*	0.00412	-0.00860	0.00434	-0.0180	-0.00397	0.00139
	(0.00559)	(0.00570)	(0.00545)	(0.00625)	(0.00632)	(0.0157)	(0.00468)	(0.00497)
lnempni	-1.870	0.742	-0.127	-0.565	-1.956	2.643	6.075***	1.630**
	(2.949)	(0.668)	(0.858)	(1.269)	(1.891)	(2.404)	(2.048)	(0.720)
lnempno	-1.615	0.0680	0.0293	0.429	-0.388	1.302	-0.887	-1.079***
	(1.371)	(0.328)	(0.366)	(0.648)	(0.737)	(0.844)	(0.540)	(0.384)
researchers_i	3.558***	2.382***	1.818***	1.191	2.742**	1.193	3.552***	3.527***
	(0.997)	(0.704)	(0.596)	(1.374)	(1.296)	(1.001)	(0.643)	(0.888)
researchers_o	2.525***	4.153***	2.711***	1.700	2.456***	4.661***	1.129*	2.265***
	(0.757)	(0.739)	(0.648)	(1.097)	(0.915)	(1.102)	(0.651)	(0.839)
lngdppc_i	4.425*	4.483**	4.465*	14.26***	3.925	1.373	-3.054*	4.992**
	(2.370)	(2.002)	(2.690)	(4.596)	(3.174)	(3.533)	(1.621)	(2.438)
lngdppc_o	5.514***	6.422***	5.765***	1.318	6.707***	5.844**	4.607**	5.272***
	(1.419)	(1.455)	(1.396)	(2.345)	(2.198)	(2.301)	(2.006)	(1.316)
lngdp_i	-4.821**	-3.985**	-4.505*	-14.29***	-2.981	-1.245	2.820*	-5.705**
	(2.445)	(1.980)	(2.630)	(4.390)	(2.953)	(3.587)	(1.574)	(2.532)
lngdp_o	-4.856***	-6.027***	-5.702***	-1.320	-6.363***	-6.247***	-3.663*	-4.773***
	(1.318)	(1.442)	(1.348)	(2.166)	(2.093)	(2.388)	(1.966)	(1.314)
Observations	22,949	29,604	28,62	27,061	20,875	22,313	26,664	25,659
Number of id	4,192	4,644	4,836	4,102	3,409	3,947	4,431	4,59
time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-0.808	-4.158	-4.628	-14.71	-2.037	-0.416	-0.807	-1.431
Observations	22,949	29,604	28,620	27,061	20,875	22,313	26,664	25,659
Number of id	4,192	4,644	4,836	4,102	3,409	3,947	4,431	4,590
time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-0.808	-4.158	-4.629	-14.71	-2.037	-0.416	-0.807	-1.431

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

B Appendix

Table 9: Poisson FE models for high-tech and low-tech sectors, dependent variable: number of forward citations that input sector-country receives from output sector-country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Input high-tech	Input low-tech	Output high-tech	Output low-tech	Input high-tech & output high-tech	Input low-tech & output low-tech	Input high-tech & output low-tech	Input low-tech & output high-tech
l_lnRD_i	0.291	0.0803	-0.350	0.104	0.258	0.0803	-0.573	-0.208
	(0.337)	(0.0975)	(0.260)	(0.0942)	(0.525)	(0.0975)	(0.365)	(0.258)
l_lnRD_bw_o	0.0116	0.0832***	1.129**	0.0730***	1.722***	0.0832***	0.0410**	0.314
	(0.0193)	(0.0176)	(0.478)	(0.0125)	(0.639)	(0.0176)	(0.0201)	(0.249)
l_lnRD_bw_osc	-1.219	1.901***	0.814	2.262***	-3.504	1.901***	1.362	1.169**
	(1.607)	(0.372)	(0.895)	(0.382)	(2.660)	(0.372)	(1.730)	(0.460)
techdist_s	0.629	-1.543***	1.056	-1.585***	-0.835	-1.543***	0.638	0.267
	(1.205)	(0.303)	(1.660)	(0.271)	(4.441)	(0.303)	(1.048)	(1.175)
techdist_c	-7.367***	-0.930*	-5.512*	-2.137***	-19.69	-0.930*	-6.194***	-0.407
	(2.362)	(0.517)	(2.953)	(0.810)	(12.53)	(0.517)	(2.364)	(1.457)
rdint_i	-0.0330***	-0.0233***	0.0151	-0.00351	-0.0444**	-0.0233***	-0.00360	-0.0391***
	(0.0122)	(0.00723)	(0.0142)	(0.00525)	(0.0177)	(0.00723)	(0.00698)	(0.0109)
rdint_o	0.00307	-0.00809	-0.0151	-0.00895	-0.0272	-0.00809	-0.0176	0.0172**
	(0.00612)	(0.00734)	(0.0148)	(0.00918)	(0.0188)	(0.00734)	(0.0116)	(0.00780)
invint_i	0.0235	0.00265*	-0.00231	0.00302	0.0268	0.00265*	-0.00712	0.00509
	(0.0143)	(0.00153)	(0.0104)	(0.00207)	(0.0231)	(0.00153)	(0.0122)	(0.00417)
invint_o	-0.00917	-0.000505	-0.00285	0.00256	0.0351	-0.000505	0.00467	-0.0302**
	(0.00838)	(0.00214)	(0.0174)	(0.00167)	(0.0277)	(0.00214)	(0.00701)	(0.0124)
lnempni	-3.862**	1.414***	-0.272	0.445	-5.143**	1.414***	0.870	2.939***
	(1.733)	(0.312)	(0.892)	(0.397)	(2.310)	(0.312)	(1.362)	(0.632)
lnempno	0.331	-0.0211	-0.856	0.524	-3.698	-0.0211	0.0115	1.744*
	(0.610)	(0.300)	(1.763)	(0.420)	(3.104)	(0.300)	(1.084)	(0.964)
researchers_i	-0.0332	2.069***	0.188	1.908***	0.133	2.069***	4.927***	2.553***
	(2.603)	(0.513)	(1.565)	(0.533)	(4.181)	(0.513)	(1.903)	(0.871)
researchers_o	-1.739	3.124***	-5.112**	2.537***	-8.705**	3.124***	-0.208	-1.745
	(1.377)	(0.571)	(2.217)	(0.491)	(3.447)	(0.571)	(0.857)	(2.083)
lngdppc_i	52.31***	3.632***	12.28***	4.625***	63.23***	3.632***	23.35***	4.439**
	(11.12)	(0.814)	(3.910)	(0.868)	(14.01)	(0.814)	(8.096)	(1.847)
lngdppc_o	4.972	4.406***	23.65	4.328***	29.57	4.406***	1.224	0.330
	(3.214)	(0.766)	(16.49)	(0.829)	(23.00)	(0.766)	(2.466)	(6.414)
lngdp_i	-51.02***	-3.667***	-12.04***	-4.447***	-62.09***	-3.667***	-22.92***	-4.673**
	(10.60)	(0.773)	(3.702)	(0.837)	(12.94)	(0.773)	(7.927)	(1.831)
lngdp_o	-4.652	-4.155***	-22.99	-4.145***	-27.97	-4.155***	-0.910	-0.548
	(3.063)	(0.715)	(16.17)	(0.769)	(22.39)	(0.715)	(2.418)	(6.231)
Observations	8,406	378,554	7,883	379,077	146	378,554	8,260	7,737
Number of id	1,159	65,047	1,101	65,105	16	65,047	1,143	1,085
time dummies	YES	YES	YES	YES	YES	YES	YES	YES
Log-likelihood	-11.16	-31.43	-11.05	-31.61	-5.886	-31.43	-5.220	-5.045

Cluster-robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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