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What determines international and inter-sectoral knowledge flows? The impact of absorptive capacity, technological distance and spillovers

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What determines international and inter-sectoral knowledge flows? The impact of absorptive capacity, technological distance and spillovers

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Abstract This paper studies determinants of knowledge flows as measured with patent forward citations that occur between 'input' and 'output sector-countries'. We look at the impact of absorptive capacity of a focal sector-country, knowledge spillovers and technological distance between sector-countries on further knowledge flows. For this purpose, we develop a knowledge flow matrix similar to input-output tables in trade where patent citations capture knowledge flows that go from the input sector-country to the output sector-country. We estimate a gravity model with variables that capture technological distance and knowledge that comes from either inside the input output pair or from external spillover sources. Our results indicate that knowledge accumulated in the output sector-country and - in some cases - external spillovers are key in generating further knowledge flows that go to the output sector-country. A distinction between high-tech and low-tech sector-countries shows that spillovers are more useful for the generation of knowledge flows if the input sector-country is low-tech. Low-tech sector-countries benefit from both high-tech knowledge from the output sector-country and external knowledge from the technological frontier. In contrast, knowledge flows based on high-tech sector-countries cannot benefit from low-tech sector-countries and only to a very limited extent from other high-tech sources. Technological distance between sector-countries has a negative impact on further knowledge flows so that only technologically proximate sector-countries are more likely to generate knowledge flows.

Keywords: Knowledge flows; Patent citations; Spillovers; Absorptive capacity; Gravity model

JEL-codes: O33.

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1 Introduction

Knowledge integration across borders and industries is an important facet of globalization and digitalization where exchange of intangible goods and also tacit knowledge across geographic and institutional borders become more and more important. The process of innovation that is to a large degree sequential relies on firms learning from external knowledge (Cohen and Levinthal 1989) and 'recombining' new-to-the-firm knowledge in meaningful ways with own knowledge (Nelson and Winter 1982; Weitzman 1998). Combining knowledge across industries seems to be prevalent: For example, in the automobile industry, some 'disruptive trends' are based on business models and technologies that have their origin in other industries such as the ICT industry (McKinsey&Company 2016). Another example is convergence of the pharmaceutical and food industry in order to produce new 'functional foods' (Hacklin et al. 2013).

External knowledge absorption partly depends on knowledge spillovers that are non-pecuniary externalities arising from others' knowledge activities and are empirically found to influence innovation and growth positively (see Coe and Helpman 1995; Griliches 1992; Jaffe 1986). The basic condition that spillovers can be absorbed is that a firm has enough absorptive capacity, i.e., that it is able to understand and exploit external knowledge and to apply it to commercial ends (Cohen and Levinthal 1989). Of course, knowledge that is absorbed from external sources might lead to further knowledge flows back to the initial sources or other firms, industries or countries after having been enriched with own knowledge and if not kept secret, thereby contributing to the process of sequential innovation.

This paper tries to disentangle different sources and recipients of knowledge and to analyse their impact on these further knowledge flows. First, it analyses determinants of knowledge flows that might arise from prior knowledge exchange between firms, industries or countries or from knowledge spillovers. Second, it takes into account whether industries that engage in the process described above are high-tech or low-tech. According to conventional wisdom, mainly high-tech industries are involved in inter-industry knowledge integration, at the same time high-tech sector-countries might act as learning sources for other less advanced sector-countries (see Griffith et al. 2004). Hence, the effects on further knowledge flows might depend to a large degree on whether the industries are high-tech or low-tech industries. We study an input output framework using a gravity-like

model with patent citations as proxies for knowledge flows and (weighted) R&D stocks as proxies for absorptive capacity and spillovers. In order to capture the direction and amount of knowledge flows between sector-countries, we emulate World Input Output Tables by counting the number of forward citations that patent applications of sector-countries (input dimension) receive from other sector-countries (output dimension) and control for industry- and country-specific factors. Beginning with Peri (2005) and Maurseth and Verspagen (2002), there are now more and more papers studying international knowledge flows in gravity models using patent citations as proxies for knowledge flows (e.g., Li 2014; Morescalchi et al. 2014).

The paper contributes to literature, both methodologically and conceptually: First, it looks at the process of knowledge generation and absorption and tries to disentangle multiple determinants of knowledge flows that might lead to more innovation and growth. The input-output framework makes it possible to distinguish between knowledge accumulated in the input and output sector-countries and spillovers from sector-countries that are external to the input and output sector-country. Second, it analyzes knowledge flows at a more detailed level than other papers on international knowledge flows, namely at the sector-country level with both an input and output dimension. The sectoral dimension is missing in existing literature to a large extent (see Badinger and Egger 2015) apart from a few notable exceptions (see Frantzen 2002; Keller 2002; Malerba et al. 2013; Park 2004). Third, the paper also includes technological distance at the sector-country and sectoral level in addition to technological distance at country level and in contrast to literature on trade and knowledge flows that is interested in a geographical dimension only.

Our results indicate that in input-output relationships, knowledge accumulated in the output sector-country is the most important source for the generation of further knowledge flows, especially when compared with own knowledge accumulated by the input sector-country. We find that knowledge spillovers from external sector-countries outside the input-output relationship are also important, but whether this kind of knowledge is used to generate further knowledge flows depends on the technological advancement of the involved sector-countries. Fully external knowledge is mainly used by low-tech input sector-countries, but the preferred source for producing knowledge flows is the high-tech output sector-country's knowledge stock (i.e., the input sector-country is low-tech and the output sector-country high-tech). Technological distance between sector-countries is found to be a major impediment of future knowledge flows between sector-country pairs, but the degree

of whether the distance between countries or the distance between industries matter again depends on the technological advancement of the respective sector-countries. In sum, the results show that knowledge flows depend to a large extent on prior knowledge exchange between sector-countries and not so much on external knowledge spillovers as suggested, but that the composition of the respective sector-country relationships greatly matters with respect to the relevance of knowledge absorption.¹

The paper is structured as follows: Section 2 gives a literature review on absorptive capacity and knowledge spillovers and states our hypotheses. Section 3 presents our empirical model and the estimation strategy. Section 4 describes the data and variables. Section 5 discusses the results and Section 6 concludes.

2 Literature review and hypotheses

2.1 Absorptive capacity and spillovers

Absorptive capacity mainly depends on past experience with R&D activities and the stock of highly-educated engineers and inventors who are able to understand external knowledge and to apply it to commercial ends. In addition, there is a continuous inflow of knowledge that spills from competitors (intra-industry spillovers), other industries or countries. A country's or industry's ability to exploit this kind of knowledge requires enough innate absorptive capacity. In Cohen and Levinthal's framework, spillovers and absorptive capacity are positively related (the more spillovers, the more absorptive capacity is needed to acquire knowledge). In addition, R&D has two faces: It stimulates innovation and establishes absorptive capacity that enables an economic entity to utilize external knowledge. Hence, the higher the absorptive capacity of firms, industries or countries, the more knowledge spillover to them will take place (Hall et al. 2010). Once internalized, spillovers also add to compound absorptive capacity by broadening the knowledge base. In this way, they may enhance further knowledge flows and innovation.

There is still little known about the potential of absorptive capacity to increase future knowledge

¹If 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.

flows, i.e. the potential not only to attract knowledge from a spillover source but also to provide the base for further knowledge flows back to the initial spillover source or another external unit.² This potential impact of absorptive capacity refers to public benefits (generation of knowledge from which others can benefit) in contrast to the private commercial benefits that are typically studied. Indeed, an economic unit that is able to recognize and utilize relevant internal and external knowledge might not only generate own inventions (and corresponding profits) out of it, but might also provide the base for knowledge that again flows to firms, industries or countries.³ Over time, the process of knowledge absorption combined with recombination, continuous improvement and enhancement of knowledge may trigger higher sequential innovative activity.

We distinguish between four potential sources of absorptive capacity and spillovers at sector-country level and examine their impact on the extent of future knowledge flows between a certain pair of sector-countries: First, the existing internal knowledge stock of an input sector-country, second, the knowledge stock of the output sector-country (that is the sector-country that cites the focal input sector-country, i.e. the sector-country that draws on the knowledge generated by the input sector-country later on), third, external knowledge spillovers from sector-countries that are external to the input sector-country (i.e., sector-countries that are not part of the input-output relationship, that do not cite the focal sector-country, but still can be used as source of spillovers initially), and, fourth, external knowledge spillovers from sector-countries that are external to the output sector-country.⁴ Knowledge from the output sector-country might be especially relevant as it is the receiver of knowledge flows later on. Knowledge that is exchanged between input and output sector-countries might be tailored to the sector-countries' needs, whereas, in the case of fully external spillovers, the knowledge is highly unspecific and only usable to some extent.

Conceptually, we distinguish between spillovers and knowledge flows in the following way: Spillovers are knowledge externalities proxied by the accumulated R&D expenditures of external sector-countries that occur involuntarily, whereas knowledge flows refer to voluntary but informal forms of knowledge exchange between an input output sector-country pair and are proxied by patent cita-

²One study that looks at knowledge flows as a function of absorptive capacity is Mukherji and Silberman (2013).

³However, in a sequential setting, knowledge flows back to the original inventor also give rise to private returns to innovation as an economic entity can benefit from the recombination of its past inventions with external ideas (Belenzon 2012; Yang et al. 2010).

⁴In the empirical implementation, the external spillovers external to either the input or output sector-country differ only with respect to their weighting scheme (see Section 3) as both include the same set of external sector-countries, namely sector-countries that are not part of the input-output relationship.

tions. Our idea is related to trade literature where firms engaging in trade relationships are found to enhance knowledge diffusion (Keller 2004; MacGarvie 2006), but there have been few attempts to study an equivalent effect of knowledge exchange through spillovers. Given our discussion and the ideas we depicted above, we can formulate the following hypotheses:

Hypothesis 1a: Knowledge accumulated in both the input sector-country and in the output sector-country exert a positive impact on further knowledge flows.

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 flows from the input to the output sector-country.

2.2 Technological distance

Literature on trade flows traditionally focuses on geographical proximity, but in the context of knowledge flows it is important to account for cognitive proximities that are represented by institutional, technological, social and organizational links between economic entities (Paci et al. 2014). In this paper, - beneath geographical distance - we focus on technological distance between industries and countries, the latter being standard in country-level studies on knowledge flows (e.g., Cappelli and Montobbio 2014; Peri 2005). In the context of technological activities, technological distance has been shown to matter most among different other cognitive distances (Paci et al. 2014). Technological distance between countries 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). At micro level, it is usually measured with the uncentered correlation between firms' patent portfolios in different technological fields (Jaffe 1986, 1989).

According to Malerba et al. (2013), technological proximity is associated with lower communication and learning costs as firms are better able to recognize and absorb knowledge that is similar to their knowledge base. Hence, the basic expectation is that a larger technological distance between economic entities decreases the probability and the extent of further knowledge flows that might occur between them and can be appropriated by the receiver. More concretely, the larger technological distance is, the less likely further knowledge flows will occur. Consequently, we expect that a larger technological distance between countries, sectors or sector-countries leads to less knowledge

flows between them.

Hypothesis 2: Technological distance between countries, sectors and sector-countries has a negative impact on further knowledge flows between an input sector-country and an output sector-country.

2.3 Low- vs. high-tech sectors

Accumulated spillovers from fully external sector-countries might stem from sector-countries that are quite heterogeneous technologically. In addition, input (sector-countries that provide knowledge) and output sector-countries (sector-countries that draw on this knowledge) can vary with respect to their technological orientation and advancement. In innovation and growth literature, high-tech countries or 'technological leaders' are considered as main growth and technological drivers. Mancusi (2008) found that only spillovers from technologically leading countries are effective in increasing innovative output. According to Peri (2005), technologically leading regions may act as learning sources for other regions. Tsai and Wang (2004) found evidence of an R&D spillover effect from the high-tech sector into traditional manufacturing industries in Taiwan. In the same vein, Hu et al. (2005) found that R&D complements technology transfer to developing countries.

In the framework of Cohen and Levinthal (1989, 1990), basic research is thought of broadening a firm's knowledge base and providing it with deeper understanding that is useful for exploiting new technical developments. Success of firms in high-tech sectors is associated with basic research to a larger degree than in low-tech sectors (Czarnitzki and Thorwarth 2012). Consequently, we expect high-tech sectors to dispose of larger knowledge bases and absorptive capacities. This accumulated knowledge can be also a useful source for others, particularly for sector-countries lagging behind the technological frontier. Griffith et al. (2004) found that such laggards catch up particularly fast if they invest heavily in R&D as building an own knowledge stock is necessary to understand knowledge from more advanced countries. The further a country lies behind the frontier, the greater the potential for R&D to increase growth of total factor productivity through technology transfer from more advanced countries. Hence, laggards can benefit disproportionately from high-tech knowledge, but at the same time they need to increase their own absorptive capacity.

Similar to countries or regions, leading high-tech sectors or sector-countries might also act as

learning source for others. We argue that knowledge spillovers should only have a positive effect on knowledge flows when the source for spillovers is a high-tech sector-country. We expect that low-tech sector-countries can learn from R&D generated in high-tech sector-countries, but - given the advanced knowledge already cumulated in a high-tech sector-country - the scope for learning for high-tech sector-countries from low-tech sector-countries should be limited. Again, we look at knowledge accumulated within the focal input-output pair and knowledge spilling from other sector-countries, being either high-tech or low-tech. In case of a focal input sector-country being low-tech, we suppose that knowledge from a high-tech output or spillovers from fully external high-tech sector-countries increase further knowledge flows. In case of a low-tech input high-tech output pair, high-tech knowledge that is first learnt by the input sector-country can flow back to the high-tech output sector-country and is utilized there. One can think about the low-tech sector-country being 'fed' with high-tech knowledge, making the low-tech sector-country a more valuable knowledge source for the output sector-country in the aftermath. This idea is summarized in the following hypotheses.

Hypothesis 3a: Knowledge accumulated in the output sector-country only exerts a positive impact on further knowledge flows from the input to the output sector-country if the output sector-country is high-tech.

Hypothesis 3b: Knowledge spillovers from external sector-countries only exert a positive impact on further input-output knowledge flows if the external sectors are high-tech.

Both low-tech and high-tech sector-countries might possess the same need to benefit from high-tech spillovers from the outset. However, we need to take into account that - on the one hand - sector-countries that are farther away from the technological frontier should benefit most since scope for learning is highest there. On the other hand, sector-countries closer to the frontier already have a higher absorptive capacity so that they may be more able to benefit from spillovers (see Aghion et al. (2009) and Miguélez and Moreno (2015), for a similar reasoning). The ease of learning of external knowledge depends on the tradeoff between the relevance of external knowledge and the complexity of this knowledge. Both relevance and complexity are expected to be higher in high-tech sector-countries. Therefore, high-tech spillovers are more relevant, but at the same time more difficult to absorb, especially for low-tech sector-countries. As a consequence, with respect

to hypotheses 3a and 3b, we have to leave open the question whether high-tech knowledge has the potential to generate further knowledge flows only if the input sector-country is high-tech or also if it is low-tech as a low-tech sector-country might lack absorptive capacity to draw on this knowledge.

3 The empirical model and estimation

We extend the models proposed by Mancusi (2008) and Peri (2005).⁵ Knowledge exchange between input and output sector-countries is assumed to benefit from their knowledge stocks (absorptive capacities) that are given by $I_{ci,si,t}$ and $I_{co,so,t}$ and knowledge spillovers that come from external sector-countries, i.e. sector-countries that are not part of the input-output relationship. For the input sector-country, the external spillovers are given by $E_{ci,si,t}$, for the output sector-country by $E_{co,so,t}$. They are proxied with the weighted sum of R&D stocks of sector-countries other than the input and output sector-country. The external stocks 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 ci, si or co, so in year t as weighting variable denoted as $\phi_{c,s,cj,sj,t}$, i.e. the ci, si or co, so 's number of backward citations of an external sector-country cj, sj in ci, si or co, so 's total backward citations. Intuitively, the more citations sector-country cj, sj receives from ci, si , the larger the likelihood that its knowledge diffuses to ci, si (Hall et al. 2010, p. 1068). Thus, external spillovers can be defined as follows:

$$E_{c,s,t} = \sum_{cj} \sum_{sj} \phi_{c,s,cj,sj,t} I_{cj,sj,t}, j \neq i, j \neq o \quad (3.1)$$

where $c = \{ci; co\}$ and $s = \{si; so\}$, depending on whether we look at spillovers external to ci, si or co, so , $\phi_{c,s,cj,sj,t}$ is the weight and $I_{cj,sj,t}$ the knowledge stock of sector-countries that are external to the input or output sector-country.⁶

We assume that citations are a noisy indicator of actual outflows and estimate a function that

⁵The whole derivations can be found in the Appendix B.1.

⁶Please 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 has to be different.

depends on the focal sector-countries' knowledge stocks (absorptive capacity), spillovers as defined above, technological distance and other gravity variables $\mathbf{x}'_{ci,si,co,so}$ for each input-output pair, industry- and country-specific variables $\mathbf{y}'_{ci,si,t}$ and $\mathbf{z}'_{co,so,t}$ for each input and output sector-country, respectively, and input and output country, industry and time fixed effects.

$$C_{ci,si,co,so,t} = \exp(\mathbf{x}'_{ci,si,co,so,t}\boldsymbol{\beta} + \mathbf{y}'_{ci,si,t}\boldsymbol{\gamma} + \mathbf{z}'_{co,so,t}\boldsymbol{\delta} + \alpha_{1i}\ln I_{ci,si,t-1} + \alpha_{1o}\ln I_{co,so,t-1} + \alpha_{2i}\ln E_{ci,si,t-1} + \alpha_{2o}\ln E_{co,so,t-1} + v_{ci} + v_{co} + v_{si} + v_{so} + v_t + \xi_{ci,si,co,so,t}) \quad (3.2)$$

For estimation, we use count data models for the number of forward citations that occur between input and output sector-countries. We estimate both Poisson models and negative binomial models (NBREG), both conditioning on random sector-country pairs (see Boesenberg and Egger (2016)).

4 Data sources, variable definitions, and descriptive statistics

4.1 Data sources

The idea to use input-output tables in order to analyze knowledge flows goes back to Scherer (1984) and has been elaborated on by Verspagen (1997) and Verspagen and De Loo (1999). 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). We use all published patents between 1995 and 2005 that can be attributed to a technological field according to the International Patent Classification (IPC, WIPO (2014)). 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)).

Transformation of technological fields according to IPC subclasses to industries based on aggregated NACE codes is accomplished with concordance data from Lybbert and Zolas (2014). We select the applicant countries and industries according to the World Input Output tables created by

Dietzenbacher et al. (2013).

We match the patent data with country-level data from World Development Indicators (The World Bank 2014) and industry-level data from the OECD STAN and ANBERD databases (OECD 2005, 2012). We end up with 22 countries and 11 industries for 1995 to 2005 that can be used in our estimations. Finally, data on geographical distances and dummies for former colonial ties, common languages and contiguities are assigned (Mayer and Zignago 2011).

4.2 Variable definition

4.2.1 Absorptive capacity and spillovers

We construct variables for absorptive capacity for each sector-country and spillovers from external sector-countries. R&D stocks are calculated based on the inventory perpetual method as described in Hall et al. (2010). We use 15% as depreciation rate. As proxy for absorptive capacity, we simply use the one-year lags of the R&D stocks that can be accrued to the focal input and output sector-country pair. For each sector-country pair, we insert the respective R&D stock for both the input and output sector-country as the knowledge flows based on the input sector-country might benefit from both knowledge stocks. We use the one-year lags of the external R&D stocks that are weighted as already described. The exact definition of $E_{ci,si,t}$ and $E_{co,so,t}$ can be found in table A.1.

4.2.2 Technological distance

Following the extant literature, we capture technological distance between sector-countries based on the correlation between their share of patents in industries and technologies. The first measure captures differences in technological specialization between two countries and is defined as follows:

$$TECHDIST_{ci,co} = 1 - SPECCORR_{ci,co} \quad (4.1)$$

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 or sector-countries are technologically close in specialization. The calculation of distances at this level is involved as both the sectoral assignment of patents and the distance measures are based on IPC (sub)classes. Therefore, we look at each industry separately (the patents were assigned to industries based on an IPC-industry concordance table beforehand), assign all IPC classes that occur in patent applications assigned to a specific sector-country (not only IPC classes that occur in the respective industry definition). Based on this assignment, we calculate distance measures for sector-countries and sectors separately for each sector-country and sector pair. The specialization index becomes $TECHDIST_{ci,si,co,so} = 1 - SPECCORR_{ci,si,co,so}$ (resp. $TECHDIST_{si,so} = 1 - SPECCORR_{si,so}$) based on the uncentered correlation between the share of patents of ci, si and co, so (resp. of si and 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). 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 A.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 percentage of researchers in R&D in a country's population 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. Finally, we insert dummy variables that take on value one if

the input and output sector, input output country or input output sector-country pairs include the same sectors, countries or sector-countries, respectively, in order to control for the possibility that citations refer heavily to the same country, sector or sector-country.

4.3 Descriptive statistics

Table A.2 shows the summary statistics for the main variables and the sample that is used in the estimations. As expected, the distributions of patent applications and especially of forward citations are very skew. Table A.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 (Hatzichronoglou 1997).⁷ The high-tech industries are indeed the industries with the highest values for the R&D stock. They also account for an above-average number of patents and forward citations.

5 Estimation results

5.1 Basic results

5.1.1 Input and output knowledge stocks

The basic results for sector-country pairs where the number of forward citations is positive can be found in table A.4.⁸ Columns (1), (3) and (5) display coefficients and standard errors from Poisson models, columns (2), (4) and (6) from NBREG. The coefficients for the (weighted) R&D stocks from both the output and external sector-countries are highly significant and positive in (1), thus suggesting significant spillover effects from external sector-countries on further knowledge flows from the input to the output sector-country. The internal R&D stock's coefficient, however, is not significant in any specification. However, the input sector-country can use knowledge from the

⁷The same classification will be used later on in the estimations for high-tech and low-tech sectors. To avoid confusion, the unit of observation is the sector-country where each sector represents a certain industry. High-tech and low-tech sectors are aggregated sectors and the definition of each comprises several industries as can be seen from Table A.3.

⁸The results from logit models where the incidence of forward citations is the binary dependent variable are shown in B.1.

output sector-country to increase absorptive capacity on which the output sector-country can build later on. Thus, hypothesis 1a receives support only with respect to knowledge from the output sector-country, hypothesis 1b on the effect of external spillovers receives strong support.

Our measures of technological distance between countries and sector-countries display significantly negative coefficients in all specifications as expected in Hypothesis 2.⁹

With respect to other variables, the number of researchers as a proxy for human capital on both the input and output side strongly increases the number of citations that input patents receive. The same is true for GDP per capita. Most of the time-invariant gravity variables show the expected signs. Notably, the coefficients of technological distance are much larger than those of geographical distance so that geographical distance is found to be of relatively low relevance for international knowledge flows.

5.1.2 External high-tech spillovers

If we look at external spillovers from high-tech sector-countries, the coefficients get larger, thus suggesting that high-tech sector-countries are valuable spillover sources for input-output knowledge flows (columns (3) and (4)).¹⁰ However, the coefficient of the remainder component (that is the ratio between total external spillovers and high-tech spillovers) is even larger and highly significant so that also non high-tech spillovers can be expected to add to the generation of further knowledge flows relative to high-tech spillovers. In columns (5) and (6) we look at what we call 'top' high-tech spillovers henceforth. These are spillovers from external sector-countries where the sectors belong to the top 10% with respect to R&D intensity.¹¹ In this case, only high-tech spillovers affect knowledge flows significantly. Thus, spillovers from external 'top' high-tech sector-countries are more relevant for the generation of further knowledge flows than high-tech spillovers based on the broader definition. However, the coefficient is smaller than in (3) and (4). In sum, the results yield

⁹The sectoral technological distance shows a positive coefficient in the NBREG, maybe due to correlation with the other distance measures.

¹⁰The decomposition of the external R&D stock in logarithm in a high-tech and a remainder component is accomplished as follows: We use formula 3.2 and look at the following part of the function that is split in a high-tech and a low-tech external stock of knowledge: $\ln(E) = \ln(E^H + E^L)$. After re-arranging, we get $\ln(E) = \ln(E^H) + \ln(\frac{E^H + E^L}{E^H})$, i.e., the external knowledge stock in logarithm now consists of the high-tech part in logarithm and the ratio between the total external stock and the high-tech stock in logarithm. Both parts are inserted separately in the regression models in order to estimate the extent of the contribution of high-tech external spillovers.

¹¹Basically, these are 'Chemicals and Chemical Products' and 'Electrical and Optical Equipment'.

mixed evidence with respect to hypothesis 3b.

5.2 Results for high-tech and low-tech sectors

5.2.1 Input and output knowledge stocks

In table A.5, we proceed by looking at knowledge flows occurring between input and output sector-countries being either both low-tech, both high-tech or one being low-tech and the other high-tech.¹² We find that the high-tech input sector-country's knowledge flows are affected by the own knowledge stock (in contrast to the results including the whole sample in Section 5.1) if the output sector-country is low-tech (column (3)) and by output knowledge if the output sector-country is also high-tech (1). Spillovers from sector-countries external to the input-sector-country play a role for both input output high-tech and input output low-tech pairs ((1) and (2)), but in (2) spillovers from sector-countries external to the output sector-country do also have an effect. Knowledge flows based on all kind of pairs benefit from the output sector-countries' knowledge stock except for input high-tech output low-tech pairs as then the input sector will avoid drawing on the low-tech knowledge stock provided by the output sector-country.

Knowledge flows based on low-tech input sector-countries benefit disproportionately from knowledge from the output sector-country if the output sector-country is high-tech (4). This indicates that the low-tech sector does better in absorbing high-tech knowledge that is familiar from prior knowledge exchange with the respective output sector-country as compared to absorbing fully external knowledge. The result is perfectly in line with hypothesis 3a. Sector-countries lagging behind the technological frontier not only catch up by learning from more advanced sector-countries, thereby enriching their own knowledge base, they also create the potential for further knowledge flows by drawing on advanced high-tech knowledge spillovers. High-tech sector-countries are thus a source of knowledge for less advanced ones. The pair considered in (4) is also the largest profiteer of spillovers external to the high-tech output sector-country. In sum, low-tech knowledge seems to benefit if combined with a broad array of other sources.

In columns (5) to (8) we use the alternative definition of high-tech sectors as described in 5.1. Some

¹²We display results from Poisson estimations only.

of the associations get stronger indicating on the one hand that 'top' high-tech knowledge is more valuable as knowledge source ((5), (7), (8)), but that this knowledge is also more difficult to draw on (see the smaller coefficients of external spillovers in (6)) for low-tech sector-countries on the other hand.

5.2.2 External high-tech and low-tech knowledge spillovers

In table A.6, we again look at external high-tech spillovers as already done in 5.1.2, but now we also account for the high-tech resp. low-tech sector affiliation of the input and output sector-country as in 5.2.1. Knowledge flows benefit from external high-tech knowledge irrespective of which input and output sector-countries are involved, but usually the effect of total spillovers relative to high-tech spillovers is also significant (columns (1)-(4)).

Looking at 'top' high-tech sector-countries and spillovers originating from there, the associations again get stronger for the input and output knowledge stocks. However, external 'top' high-tech spillovers seem only to matter when the input sector-country is low-tech ((6) and (8)). In contrast, the input 'top' sector-countries solely draw on input (7) or output (5) high-tech knowledge.

From the outset, it was not clear whether low-tech sector-countries have enough absorptive capacity in order to absorb more advanced knowledge. The results indicate that knowledge flows can be generated based on low-tech sector-countries if combined with output high-tech knowledge or by combining a wide array of external sources (that are associated with the output sector-country though). Although it seems to be more convenient to draw on output high-tech sector-countries' knowledge stocks directly, we found some evidence that knowledge generation based on low-tech sector-countries also benefit from external 'top' knowledge sources.

In sum, external high-tech spillovers only have the potential to generate further knowledge flows in some cases, namely in combination with other external sources or if constrained to 'top' sector-countries as originators. For low-tech input sector-countries, drawing on knowledge from either an output or external high-tech sectors can generate a broader knowledge base and stimulate own knowledge activities, but the association with the output knowledge stock is generally much stronger.

5.3 Results for different industries

5.3.1 Input and output knowledge stocks and external knowledge spillovers

In this section, we gather further insights into industry specificities with respect to knowledge generation and absorption. To this end, we run the estimations for each input industry separately, not summarizing single industries into high-tech or low-tech sectors. Tables A.7a and A.7b show the results for selected low-tech industries and high-tech input industries. Knowledge flows originating in most of the low-tech industries seem to hinge on output knowledge and spillovers external to the respective output sector. In two of the low-tech industries considered here, the internal knowledge stock exerts a negative effect on knowledge flows indicating that the low-tech stock creates a barrier for further flows and the sector-country's ability to generate further knowledge flows depends on output and external knowledge. Interestingly, except for 'Electrical and Optical Equipment' (column (b)(3)), all high-tech industries are 'introverted' and external knowledge absorption does not play any role for further knowledge flows.¹³ In sum, the results support the notion that external knowledge absorption is particularly important for low-tech sectors as knowledge generated there can benefit from external knowledge. For technological distance, sectoral distance dominates in low-tech industries, whereas country-level distance seems to dominate in high-tech industries.¹⁴ High-tech industries are already operating at the frontier, but there might be still differences across countries creating barriers for knowledge absorption.

In Figures 1 and 2 we go into even deeper detail by looking at industry-industry pairs separately. We display significant coefficients at the 10% significance level for selected input industries, all possible output industries and the following variables: knowledge stocks of the output industry, technological distance at sector-country level, spillovers from external industries (input side) and spillovers from external industries (output side).¹⁵ The results suggest that (12) 'Machinery' is the

¹³This finding is not in line with findings from Belenzon (2012) who found that innovation in the Electronics industry is more cumulative so that fully external knowledge is less valuable. Malerba et al. (2013) argue that international intrasectoral knowledge spillovers are particularly relevant for the Electronics industry that is globalized to a large degree, but in contrast to us they found that national inter-sectoral knowledge spillovers are relevant for the Machinery industry and national, inter-sectoral knowledge spillovers for the Chemical industry.

¹⁴However, geographic distance is not relevant in high-tech industries.

¹⁵For example, the results in Figure 1 for input external spillovers should be read as follows: 'If the input industry is 'Agriculture (...)' and the output industry (12) 'Machinery', we find a significantly positive spillover effect from external high-tech industries (i.e., industries that are not 'Agriculture (...)' or 'Machinery') on further knowledge flows between those industries. In addition, we find a positive association between the 'Machinery' output knowledge

most important high-tech output knowledge source for low-tech industries. In addition, for low-tech industries' knowledge flows, the elasticities of output high-tech knowledge stocks are usually larger in magnitude than output low-tech sources. For high-tech industries, relationships with the output industry (and also with other high-tech industries) seem to be of lower relevance for the generation of knowledge flows. Knowledge flows based on the 'Electrical and Optical Equipment' industry benefit most from output knowledge when the output industry is the same industry. Interestingly, most of the low-tech industries' knowledge flows are increased by additional external input spillovers even if the output industry is high-tech, suggesting that recombination of knowledge depends on a large variety of sources. In some cases, high-tech industries also complement their knowledge base with appropriate external high-tech or even low-tech knowledge, but the coefficients are generally much smaller than for low-tech industries.

5.3.2 External high-tech and low-tech knowledge spillovers

We again distinguish between external high-tech and low-tech knowledge spillovers (see Tables A.8a-A.9b). For three out of four low-tech industries, the spillovers seem to be attributable to 'top' high-tech knowledge from sector-countries external to the output sector. 'Electrical and Optical Equipment' is the only high-tech industry where knowledge flows generally benefit from spillovers from other high-tech industries rather than from other industries.

5.4 Robustness of results

We provide two additional robustness checks.¹⁶ First, we check whether the results are driven by sector-country pairs that consist of the same input and output sector, country or sector-country although we already control for these pairs with dummies. In sum, the results are not affected if we only include sector-countries, sectors or countries that are different from each other.

Second, we check whether the inclusion of "patent scope" and "number of claims" change our results. 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

stock and further knowledge flows between this industry pair.'

¹⁶Results are not shown.

patent makes. Both indicators are associated with value and quality of a patent (see Squicciarini et al. 2013). 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.

6 Conclusions

In this paper, we look at international and inter-sectoral knowledge flows between sector-countries as measured with patent citations. We use a very detailed dataset that goes down to the sector-country input output level. We add to literature by analyzing the effect of absorptive capacity and knowledge spillovers on further knowledge flows that occur between a sector-country pair, by considering technological distance at the sectoral, sector-country and country level, and by providing a detailed analysis for sectors of different technological advancement. This analysis helps to partly resolve the heterogeneity involved in the process of knowledge absorption and generation in an international and inter-sectoral context and to shed light on informal knowledge relationships between technologically diverse input output sector-countries.

The basic estimations show that technological distance, knowledge from output and spillovers from external sector-countries are important drivers of further knowledge flows between input and output sector-countries, but that the output sector-country is very often the most important source of knowledge. Knowledge exchange between input-output sector-countries seems to be mainly a self-sustaining process at first sight where the output sector-country draws on knowledge recombined by the input sector-country but provided by the output sector beforehand. External knowledge spillovers play an important but more limited role in adding to the own knowledge base and generating the basis for further knowledge flows to the output sector. In general, knowledge accumulated in the output sector and external spillovers from sector-countries external to the input or output sector-countries turn out to be more important than the internal knowledge stock of the input sector-country for follow-up knowledge flows.

Estimating the models for input and output sector-countries with different high-tech and low-tech sector affiliations shows that the absorption and utilization of external knowledge spillovers vary

across sectors. First, for knowledge flows originating in a low-tech sector-country, drawing on a variety of external knowledge sources (and especially knowledge from the technological frontier) is relatively important. Second, knowledge flows originating in a high-tech sector-country benefit less from enrichment with external high-tech knowledge and absolutely not from external low-tech spillovers. The process of knowledge absorption and generation in high-tech industries seem to take place more in isolation - although high-tech industries have a larger potential to absorb and utilize knowledge from various sources given their high absorptive capacity -, whereas in low-tech industries, learning from a variety of knowledge sources and especially from 'top' high-tech knowledge is prevalent. Third, knowledge flows based on a low-tech sector-country can benefit most from high-tech knowledge coming directly from the output sector-country. This channel might provide more familiar knowledge than drawing on unspecific spillovers. A high-tech high-tech input-output pair is the only constellation where the the impact of the output knowledge stock is even larger in magnitude. The knowledge that is first learnt and then recombined by low-tech sector-countries is only valuable for high-tech sector-countries if it is enriched with more advanced knowledge.

Convergence of knowledge across industries that might lead to new, disruptive technologies and products is a well-known phenomenon but its determinants and impacts are poorly understood. The results for high-tech and low-tech sector-countries show that it is mainly established knowledge relationships that thrive further knowledge generation and absorption. Integrating external knowledge is of relatively low importance when industries with more advanced technologies are the direct or indirect receivers of spillovers.

From a policy point of view, the finding that the knowledge flows from most of the high-tech industries do not depend on external knowledge is striking. Obviously, for these industries, only highly specialized knowledge is relevant that might not be available from the external sources considered here. The question arises whether sequential innovation performance in these sector-countries could benefit from more knowledge exchange with external sector-countries and also how low-tech sector-countries could be supported in adopting and using knowledge from the technological frontier.

The major limitation of this study lies in the fact that we use patent citations as proxy for knowledge flows. Although we apply common measures used in literature, the well-known limitations of patent data apply. Unfortunately, data embodying knowledge exchange through labor turnover or migration of knowledge workers is only available in very limited contexts and difficult to obtain at

our level of analysis. A further limitation is that we are only able to trace a very limited part of the sequential innovation process. Future research might try to take into account the sequentiality and complexities of knowledge flows and the underlying processes using appropriate methods. It would also help to further refine the empirical analysis by providing firm-level evidence and examining productivity effects of knowledge flows that are based on previous knowledge accumulation and spillovers. Finally, a well-developed theoretical framework for the impact of absorptive capacity and spillovers on further knowledge flows would help understand the underlying processes and interdependencies.

A Tables

Table A.1: Description of variables

Variables	Description
C	Number of forward citations within 5 years after publication of patent applications in input sector-country ci, si by output sector-country so, co in year t
$\ln I_i$	R&D stock of ci, si in $t - 1$ in natural logarithm
$\ln I_o$	R&D stock of co, so in $t - 1$ in natural logarithm
$\ln E_i$	Weighted sum of R&D stocks of $cj, sj, t - 1$, $(cj, sj) \neq (co, so)$, $(cj, sj) \neq (ci, si)$, weighted with relative backward citations from ci, si to cj, sj in natural logarithm
$\ln E_o$	Weighted sum of R&D stocks of $cj, sj, t - 1$, $(cj, sj) \neq (co, so)$, $(cj, sj) \neq (ci, si)$, weighted with relative backward citations from co, so to cj, sj in natural logarithm (Relative backward citations are the number of backward citations from $c, s, t - 1$ to $cj, sj, t - T$ divided by the total number of backward citations of $c, s, t - 1$ where $T > 1$ and $s = \{si; so\}$ and $c = \{ci; co\}$).
rdint	R&D intensity in ci, si, t and co, so, t
invint	Investment intensity in ci, si, t and co, so, t
lnempln	Natural logarithm of number of employees in ci, si, t and co, so, t
researcher	Researchers in R&D in % 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 17 industries)
techdist_s	Technological distance between si, t and so, t (uncentered correlation coefficient between the share of patents of si, t and so, t in the underlying technological fields)
techdist_cs	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)
ldist	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 A.2: Summary statistics for sector-countries with positive number of C

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) p50	(6) max
C_t	399,476	62.33	3,161.37	0.00	0.47	876,566.94
$patent_count_t$	399,476	7,972.25	21,672.87	1.05	1,716.45	261,053.13
lnI_t	398,815	19.96	2.68	0.00	20.00	26.49
lnE_t	398,815	22.22	5.44	0.00	23.52	25.46
$techdist_{si,so,t}$	399,476	0.64	0.26	0.00	0.70	0.98
$techdist_{ci,co,t}$	399,476	0.10	0.09	0.00	0.08	0.47
$techdist_{ci,si,co,so,t}$	399,476	0.70	0.24	0.00	0.77	1.00
$rdint_t$	399,476	3.47	5.95	0.00	1.23	48.35
$invint_t$	399,476	19.34	12.85	2.30	16.48	210.08
$lnmpnt_t$	399,476	11.90	1.48	4.48	11.98	16.06
$lngdp_t$	399,476	27.25	1.28	24.04	27.44	30.20
$lngppc_t$	399,476	10.11	0.31	8.99	10.16	10.70
$researcherst_t$	399,476	0.29	0.14	0.10	0.28	0.80
$lndist$	399,476	7.37	1.32	3.98	7.28	9.81

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

si	C		$patent_count_{si,t}$		$lnI_{ci,si,t}$	
	Mean	Sd	Mean	Sd	Mean	Sd
<i>Low-tech sectors</i>						
Agriculture, Hunting, Forestry and Fishing	23.1	218.2	5,380.2	7,920.9	17.9	3.2
Mining and Quarrying	21.2	185.8	5,575.2	8,894.2	17.6	3.5
Food, Beverages and Tobacco	36.9	708.5	5,766.7	9,792.8	20.2	1.6
Textiles and Textile Products and Leather, Leather and Footwear	36.2	587.2	8,739.2	12,338.6	19.0	1.3
Wood and Products of Wood and Cork	3.2	30.8	859.0	1,149.2	17.4	2.2
Pulp, Paper, Printing and Publishing	33.4	594.5	4,468.0	6,864.8	19.2	1.8
Coke, Refined Petroleum and Nuclear Fuel	16.6	230.5	1,928.1	2,765.7	20.0	2.0
Rubber and Plastics	13.0	139.0	1,849.3	2,765.4	20.2	1.5
Other Non-Metallic Mineral	17.7	201.1	2,454.5	3,521.5	19.4	1.8
Basic Metals and Fabricated Metal	69.8	1,179.6	9,530.4	15,449.3	20.5	1.6
Manufacturing, nec; Recycling	9.1	115.7	1,623.2	2,466.4	18.8	2.6
Electricity, Gas and Water Supply	14.3	157.6	2,427.5	3,503.8	19.1	3.1
Construction	28.2	316.7	5,249.6	7,111.6	18.8	2.2
<i>High-tech sectors</i>						
Chemicals and Chemical Products	132.9	2,243.1	18,535.0	35,287.1	22.2	1.8
Machinery, nec	83.9	1,444.9	12,152.6	20,252.3	21.2	1.7
Electrical and Optical Equipment	365.8	11,580.8	31,308.1	59,384.2	22.9	1.8
Transport Equipment	46.0	545.3	6,575.0	9,053.2	22.4	2.4
Total	30.3	2,209.5	4,907.8	16,457.9	19.0	3.3
ci	C		$patent_count_{ci,t}$		$lnI_{ci,si,t}$	
	Mean	Sd	Mean	Sd	Mean	Sd
AT	5.1	26.3	10,682.0	458.5	19.2	1.7
AU	2.5	8.3	8,508.6	2,073.7	19.3	0.5
BE	7.4	52.3	8,179.6	1,013.1	19.6	1.6
CA	27.3	485.5	21,500.2	3,652.9	20.5	1.3
CZ	0.7	2.9	2,448.0	169.8	18.3	1.8
DE	100.7	688.6	188,960.2	15,506.0	21.5	1.8
ES	3.4	20.2	13,742.9	1,376.6	20.0	1.3
FI	5.9	37.1	16,177.0	1,242.0	18.8	1.3
FR	28.8	253.2	70,182.6	5,204.7	21.5	1.6
GB	29.7	326.2	48,142.0	2,936.2	21.5	1.6
GR	0.4	1.9	344.7	37.7	17.4	1.0
HU	0.8	5.1	2,407.1	284.8	16.8	2.6
IE	2.7	26.8	2,701.6	348.4	17.7	2.3
IT	8.8	57.4	25,401.3	1,969.7	19.9	2.9
KR	43.8	731.4	104,958.3	51,878.2	20.6	1.8
NL	22.5	220.1	30,191.2	6,536.6	19.8	1.6
PL	0.8	5.1	5,084.3	498.2	18.8	1.2
PT	0.4	2.0	526.4	111.9	17.4	1.2
SI	0.5	2.0	611.5	140.8	16.4	2.8
SK	0.5	2.2	436.6	52.2	11.9	8.2
US	609.9	12,256.9	410,550.0	57,957.4	23.3	1.7
Total	30.3	2,209.5	45,547.7	88,706.3	19.0	3.3

Table A.4: Count-data models, dependent variable: number of forward citations that input sector-country receives from output sector-country

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Poisson fw_cit5	NBREG fw_cit5	Poisson fw_cit5	NBREG fw_cit5	Poisson fw_cit5	NBREG fw_cit5
l.lnI_i	0.040 (0.058)	-0.003 (0.003)	0.018 (0.058)	-0.003 (0.003)	0.046 (0.061)	-0.003 (0.003)
l.lnI_o	0.151*** (0.043)	0.003 (0.003)	0.141*** (0.041)	0.003 (0.003)	0.158*** (0.049)	0.003 (0.003)
l.lnE_i	0.013*** (0.003)	0.009*** (0.001)				
l.lnE_o	0.013*** (0.003)	0.009*** (0.001)				
l.lnE_high_i			0.035*** (0.008)	0.014*** (0.001)		
l.lnE_high_ratio_i			0.974*** (0.340)	0.225*** (0.029)		
l.lnE_high_o			0.013 (0.011)	0.012*** (0.001)		
l.lnE_high_ratio_o			0.015 (0.455)	0.110*** (0.019)		
l.lnE_high_top_i					0.014*** (0.003)	0.009*** (0.001)
l.lnE_high_top_ratio_i					-0.003 (0.043)	0.003 (0.003)
l.lnE_high_top_o					0.014*** (0.003)	0.009*** (0.001)
l.lnE_high_top_ratio_o					-0.037 (0.056)	0.008*** (0.003)
rdint_i	0.008 (0.008)	0.002*** (0.001)	0.006 (0.008)	0.002*** (0.001)	0.008 (0.008)	0.002*** (0.001)
rdint_o	0.001 (0.008)	0.001** (0.001)	0.000 (0.008)	0.001** (0.001)	0.001 (0.008)	0.002** (0.001)
invint_i	0.001 (0.003)	-0.001*** (0.000)	0.000 (0.003)	-0.001*** (0.000)	0.001 (0.003)	-0.001*** (0.000)
invint_o	-0.001 (0.003)	-0.001*** (0.000)	-0.002 (0.003)	-0.001*** (0.000)	-0.001 (0.003)	-0.001*** (0.000)
lnempn_i	-0.108 (0.160)	0.057*** (0.009)	-0.003 (0.167)	0.058*** (0.009)	-0.127 (0.188)	0.057*** (0.009)
lnempn_o	-0.158 (0.169)	0.068*** (0.009)	-0.123 (0.171)	0.068*** (0.009)	-0.191 (0.202)	0.068*** (0.009)
researchers_i	2.517*** (0.514)	0.787*** (0.075)	2.519*** (0.504)	0.786*** (0.075)	2.516*** (0.515)	0.787*** (0.075)
researchers_o	1.834*** (0.436)	0.596*** (0.075)	1.825*** (0.429)	0.591*** (0.075)	1.839*** (0.437)	0.596*** (0.075)
lngdppc_i	7.117*** (0.929)	1.950*** (0.165)	7.668*** (0.936)	2.002*** (0.165)	7.016*** (0.959)	1.942*** (0.165)
lngdppc_o	6.338*** (0.837)	1.342*** (0.161)	6.427*** (0.837)	1.372*** (0.161)	6.053*** (0.870)	1.339*** (0.161)
lngdp_i	-6.091*** (0.823)	-1.641*** (0.145)	-6.624*** (0.825)	-1.691*** (0.146)	-5.990*** (0.810)	-1.634*** (0.146)
lngdp_o	-4.882*** (0.797)	-0.741*** (0.142)	-4.998*** (0.813)	-0.768*** (0.142)	-4.616*** (0.752)	-0.737*** (0.142)
techdist_s	-0.772 (0.536)	0.122*** (0.031)	-0.699 (0.458)	0.117*** (0.031)	-0.693 (0.616)	0.134*** (0.031)
techdist_cs	-1.394*** (0.292)	-0.490*** (0.028)	-1.392*** (0.282)	-0.491*** (0.028)	-1.390*** (0.292)	-0.490*** (0.028)
techdist_c	-2.232*** (0.678)	-1.050*** (0.052)	-2.116*** (0.672)	-1.049*** (0.052)	-2.238*** (0.680)	-1.051*** (0.052)
lndist	-0.170*** (0.018)	0.032*** (0.006)	-0.174*** (0.018)	0.032*** (0.006)	-0.169*** (0.018)	0.032*** (0.006)
contig	0.166*** (0.023)	0.206*** (0.016)	0.167*** (0.023)	0.206*** (0.016)	0.167*** (0.024)	0.206*** (0.016)
comlang_off	0.171*** (0.021)	0.153*** (0.016)	0.169*** (0.021)	0.153*** (0.016)	0.174*** (0.022)	0.152*** (0.016)
colony	0.059*** (0.022)	-0.005 (0.017)	0.061*** (0.022)	-0.004 (0.017)	0.057** (0.024)	-0.004 (0.017)
c_pair	2.338*** (0.054)	0.378*** (0.019)	2.341*** (0.053)	0.378*** (0.019)	2.349*** (0.058)	0.378*** (0.019)
s_pair	0.680** (0.315)	0.106*** (0.018)	0.738*** (0.272)	0.107*** (0.018)	0.715** (0.357)	0.111*** (0.018)
cs_pair	0.112 (0.102)	-0.072** (0.033)	0.088 (0.086)	-0.074** (0.033)	0.125 (0.115)	-0.071** (0.033)
Observations	399,476	399,476	399,476	399,476	399,476	399,476
Log-likelihood	-2.390e+06	-751758	-2.384e+06	-751716	-2.388e+06	-751750
Wald chi2	270148	59715	272871	59849	260956	59742

Cluster robust standard errors in parentheses, constants are suppressed.

Time, input sector, output sector, input country and output country dummies are always included.

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

Table A.5: Poisson 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) & output high-tech	(2) Input low-tech & output low-tech	(3) Input high-tech & output low-tech	(4) Input low-tech & output high-tech	(5) Input 'top' high-tech & output low-tech	(6) Input low-tech & output low-tech	(7) Input 'top' high-tech & output low-tech	(8) Input low-tech & output 'top' high-tech
l.lnI_i	-0.026 (0.316)	-0.005 (0.022)	0.494*** (0.161)	-0.079 (0.061)	0.221 (0.499)	-0.028 (0.028)	1.071*** (0.301)	-0.083 (0.086)
l.lnLo	0.873*** (0.243)	0.032* (0.018)	-0.051 (0.063)	0.522*** (0.142)	1.552*** (0.418)	0.063** (0.026)	-0.041 (0.074)	0.640*** (0.234)
l.lnE_i	0.013*** (0.005)	0.019** (0.007)	0.010 (0.009)	0.002 (0.008)	0.005 (0.008)	0.009** (0.004)	0.016 (0.010)	0.002 (0.008)
l.lnE_o	0.003 (0.004)	0.017*** (0.005)	0.007 (0.006)	0.022*** (0.008)	0.002 (0.006)	0.016*** (0.004)	0.004 (0.005)	0.025*** (0.009)
rdint_i	0.007 (0.008)	0.071** (0.030)	-0.012 (0.014)	0.088*** (0.032)	-0.006 (0.005)	-0.002 (0.013)	-0.015 (0.022)	-0.009 (0.022)
rdint_o	-0.010 (0.007)	0.055* (0.029)	0.095* (0.057)	0.002 (0.014)	-0.006 (0.005)	-0.007 (0.010)	0.026 (0.032)	-0.004 (0.015)
invint_i	0.002 (0.006)	0.001 (0.002)	0.017** (0.008)	0.002 (0.002)	0.013** (0.006)	0.002 (0.002)	0.013** (0.008)	0.002 (0.003)
invint_o	0.005 (0.006)	-0.002 (0.002)	0.002 (0.003)	0.001 (0.007)	-0.001 (0.007)	0.001 (0.003)	0.003 (0.003)	-0.003 (0.006)
lnempn_i	-0.346 (0.390)	0.104 (0.094)	0.054 (0.303)	0.120 (0.146)	-0.365 (0.485)	0.095 (0.104)	-0.427 (0.456)	0.408** (0.184)
lnempn_o	-0.494 (0.414)	-0.015 (0.090)	-0.058 (0.182)	0.002 (0.201)	-0.875* (0.531)	0.003 (0.103)	0.126 (0.279)	0.106 (0.243)
researchers_i	2.408*** (0.819)	2.881*** (0.494)	2.070*** (0.787)	1.464* (0.799)	0.803 (1.228)	2.625*** (0.366)	0.893 (1.025)	1.124 (0.765)
researchers_o	0.153 (0.887)	2.247*** (0.475)	1.132* (0.583)	1.363** (0.620)	-1.426 (1.377)	1.930*** (0.358)	0.990 (0.685)	0.735 (0.687)
lngdppc_i	8.655*** (2.410)	6.456*** (1.068)	4.535** (2.245)	8.562*** (1.264)	10.532*** (3.701)	6.403*** (0.833)	8.224*** (2.681)	9.671*** (1.495)
lngdppc_o	7.491*** (2.307)	8.071*** (0.280)	5.249*** (0.774)	5.949*** (1.372)	10.733*** (3.683)	7.834*** (0.804)	4.872*** (1.680)	7.337*** (1.630)
lngdp_i	-7.593*** (2.241)	-5.363*** (0.971)	-4.000** (1.853)	-6.600*** (1.295)	-10.187*** (3.693)	-4.974*** (0.762)	-7.889*** (2.20)	-7.667*** (1.393)
lngdp_o	-6.237*** (2.273)	-6.486*** (1.000)	-4.200*** (1.358)	-4.841*** (1.160)	-9.563*** (3.697)	-6.197*** (0.728)	-3.933*** (1.401)	-6.232*** (1.339)
techdist_s	0.334 (2.387)	-1.640*** (0.280)	-0.300 (0.774)	-1.887*** (0.553)	-8.623 (6.395)	-1.267*** (0.359)	-0.183 (0.723)	-1.191* (0.480)
techdist_cs	-1.817** (0.872)	-1.349*** (0.169)	-1.364*** (0.455)	-0.672* (0.399)	0.536 (1.346)	-1.463*** (0.203)	-1.355** (0.571)	-1.480*** (0.526)
techdist_c	-3.468*** (1.253)	-1.428*** (0.301)	-1.198* (0.633)	-0.236 (1.517)	-3.793** (1.502)	-0.790*** (0.278)	-1.404* (0.792)	-0.250 (0.658)
Indist	-0.155*** (0.045)	-0.200*** (0.012)	-0.203*** (0.025)	-0.211*** (0.023)	-0.143** (0.072)	-0.205*** (0.159***)	-0.202*** (0.031)	-0.211*** (0.028)
contig	0.146 (0.091)	0.123*** (0.022)	0.131** (0.052)	0.203*** (0.050)	0.009 (0.119)	0.159*** (0.021)	0.127* (0.067)	0.206*** (0.068)
comlang_off	0.173** (0.072)	0.168*** (0.023)	0.234*** (0.042)	0.193*** (0.041)	0.262*** (0.101)	0.168*** (0.020)	0.209*** (0.052)	0.164*** (0.053)
colony	0.028 (0.072)	0.077*** (0.024)	0.076* (0.044)	0.086** (0.041)	0.056 (0.115)	0.083*** (0.020)	0.132*** (0.058)	0.148*** (0.057)
c.pair	2.315*** (0.137)	2.278*** (0.040)	2.422*** (0.086)	2.582*** (0.081)	2.788*** (0.273)	2.382*** (0.037)	2.459*** (0.105)	2.583*** (0.099)
s.pair	1.412 (1.712)	0.108 (0.180)			-3.675 (5.141)	0.309 (0.212)		
es.pair	0.043 (0.183)	0.153* (0.087)			-0.272 (0.290)	0.129 (0.083)		
Observations	28,697	218,795	75,928	76,056	7,804	345,701	45,971	45,989
Log-likelihood	-59804	-671057	-535082	-503795	-313291	-1.500e+06	-459333	-428626
Wald chi2	57155	143799	71093	75724	47833	243671	56387	56479

Cluster robust standard errors in parentheses, constants are suppressed.
Time, input sector, output sector, input country and output country dummies are always included.
*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Poisson 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 & output high-tech	(2) Input low-tech & output low-tech	(3) Input high-tech & output low-tech	(4) Input low-tech & output high-tech	(5) Input 'top' high-tech & output 'top' high-tech	(7) Input 'top' high-tech & output low-tech	(8) Input low-tech & output 'top' high-tech
l.lnLi	-0.083 (0.311)	-0.003 (0.021)	0.362*** (0.135)	-0.080 (0.509)	0.224 (0.507)	0.971*** (0.028)	-0.079 (0.084)
l.lnLo	0.846*** (0.243)	0.029 (0.018)	-0.053 (0.062)	0.435*** (0.123)	1.565*** (0.438)	-0.043 (0.074)	0.705*** (0.154)
l.lnE.high_i	0.033*** (0.011)	-0.039 (0.044)	0.041** (0.017)	0.027 (0.022)	0.007 (0.005)	0.005 (0.005)	0.027*** (0.010)
l.lnE.high_ratio_i	0.986*** (0.392)	-2.119 (1.639)	1.342** (0.657)	0.978 (0.765)	-0.081 (0.112)	0.008 (0.104)	-0.116 (0.206)
l.lnE.high_o	0.002 (0.011)	0.077* (0.042)	0.057*** (0.018)	0.047*** (0.012)	-0.006 (0.005)	-0.001 (0.013)	-0.006 (0.022)
l.lnE.high_ratio_o	-0.091 (0.421)	2.197 (1.543)	1.953*** (0.688)	1.107** (0.559)	1.107** (0.559)	0.010** (0.004)	0.003 (0.008)
l.lnE.high_top_i							
l.lnE.high_top_ratio_i							
l.lnE.high_top_o							
l.lnE.high_top_ratio_o							
rdint_i	0.006 (0.007)	0.073** (0.030)	-0.013 (0.014)	0.084** (0.033)	0.008 (0.007)	0.016 (0.011)	0.003 (0.008)
rdint_o	-0.009 (0.007)	0.052* (0.029)	0.090 (0.055)	0.001 (0.015)	-0.033 (0.069)	0.160 (0.227)	0.251** (0.125)
invint_i	0.000 (0.006)	0.001 (0.002)	0.014** (0.007)	0.002 (0.002)	0.007 (0.006)	0.005 (0.005)	0.027*** (0.003)
invint_o	0.004 (0.006)	-0.002 (0.002)	0.001 (0.003)	-0.002 (0.006)	0.001 (0.007)	0.003 (0.003)	-0.001 (0.005)
lnmnpn_i	-0.132 (0.409)	0.101 (0.093)	0.308 (0.306)	0.147 (0.141)	-0.399 (0.504)	-0.257 (0.606)	0.439** (0.187)
lnmnpn_o	-0.485 (0.428)	-0.012 (0.089)	-0.023 (0.184)	0.190 (0.208)	-0.934 (0.571)	0.121 (0.277)	-0.007 (0.340)
researchers_i	2.496*** (0.830)	2.837*** (0.493)	2.236*** (0.767)	1.432* (0.800)	0.823 (1.198)	1.058 (0.912)	1.010 (0.789)
researchers_o	0.217 (0.849)	2.287*** (0.471)	1.144** (0.582)	1.451** (0.624)	-1.359 (1.322)	0.751 (0.690)	0.910 (0.678)
lngdppc_i	9.004*** (2.370)	6.490*** (1.064)	4.618** (2.305)	8.876*** (1.292)	10.012*** (3.570)	8.826*** (2.500)	9.880*** (1.466)
lngdppc_o	7.509*** (2.254)	8.086*** (1.077)	5.621*** (1.498)	5.946*** (1.344)	9.561*** (3.335)	4.884*** (1.710)	6.619*** (1.500)
lngdp_i	-7.948*** (2.181)	-5.397*** (0.967)	-4.113** (1.914)	-6.930*** (1.346)	-9.740*** (3.562)	-8.381*** (2.105)	-7.790*** (1.388)
lngdp_o	-6.273*** (2.219)	-6.495*** (0.989)	-4.596*** (1.268)	-4.867*** (1.131)	-8.491*** (3.285)	-3.950*** (1.407)	-5.596*** (1.378)
techdist_s	0.580 (1.929)	-1.633*** (0.279)	0.003 (0.808)	-1.693*** (0.578)	-7.215 (6.519)	-0.197 (0.909)	-1.208* (0.716)
techdist_cs	-1.760** (0.838)	-1.354*** (0.169)	-1.433*** (0.431)	-0.745* (0.401)	-1.490*** (1.361)	-1.386** (0.553)	-1.397*** (0.520)
techdist_c	-3.378*** (1.252)	-1.431*** (0.297)	-1.001 (0.639)	-0.104 (0.282)	-3.705** (1.469)	-1.410* (0.795)	-0.344 (0.660)
Indist	-0.157*** (0.046)	-0.200*** (0.012)	-0.203*** (0.025)	-0.211*** (0.023)	-0.130* (0.077)	-0.205*** (0.011)	-0.209*** (0.028)
contig	0.157* (0.093)	0.123*** (0.022)	0.141*** (0.054)	0.209*** (0.051)	0.028 (0.122)	0.128* (0.068)	0.199** (0.068)
comlang_off	0.171** (0.072)	0.169*** (0.023)	0.226*** (0.042)	0.188*** (0.042)	0.278** (0.108)	0.209*** (0.052)	0.166*** (0.052)
colony	0.035 (0.073)	0.076*** (0.024)	0.078** (0.045)	0.087** (0.042)	0.039 (0.129)	0.134*** (0.058)	0.145*** (0.056)
c.pair	2.311*** (0.132)	2.278*** (0.040)	2.442*** (0.087)	2.594*** (0.082)	2.918*** (0.338)	2.455*** (0.105)	2.581*** (0.098)
s.pair	1.740 (1.427)	0.109 (0.179)	-5.086 (5.580)	0.319 (0.214)	0.319 (5.580)	0.319 (0.214)	0.319 (0.214)
cs.pair	0.060 (0.181)	0.154* (0.087)	0.154* (0.087)	0.126 (0.083)	0.126 (0.304)	0.126 (0.083)	0.126 (0.083)
Observations	28,697	218,955	75,928	76,056	7,804	45,971	45,989
Log-likelihood	-594991	-670863	-532575	-502553	-311206	-458889	-427867
Wald chi2	54412	144216	70210	75482	45327	56184	59197

Cluster robust standard errors in parentheses, constants are suppressed.
Time, input sector, output sector, input sector and output country dummies are always included.
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1)	(2)	(3)	(4)
l.lnI_i	-0.037 (0.054)	-0.091*** (0.032)	0.351*** (0.120)	-0.125*** (0.046)
l.lnI_o	0.095* (0.052)	0.128*** (0.039)	0.286*** (0.092)	0.086** (0.041)
l.lnE_i	-0.205 (0.251)	-0.021 (0.190)	0.766*** (0.213)	0.005 (0.003)
l.lnE_o	0.014** (0.006)	0.024*** (0.004)	0.022*** (0.007)	0.004 (0.004)
rdint_i	0.315** (0.135)	0.146 (0.091)	-0.026 (0.092)	-0.171 (0.114)
rdint_o	-0.016 (0.011)	-0.013 (0.011)	0.006 (0.013)	-0.012 (0.011)
invint_i	-0.009 (0.013)	0.003 (0.006)	-0.020 (0.013)	0.008 (0.013)
invint_o	0.007* (0.004)	0.004 (0.005)	0.006 (0.007)	0.006 (0.004)
lnempn_i	-0.275 (0.318)	0.059 (0.103)	2.643*** (0.360)	-0.487** (0.229)
lnempn_o	0.496*** (0.174)	0.321*** (0.079)	0.736*** (0.246)	0.140 (0.202)
researchers_i	-2.028 (1.287)	3.843*** (0.381)	3.029*** (1.132)	4.518*** (0.661)
researchers_o	0.463 (0.849)	2.382*** (0.418)	2.329** (1.038)	2.315*** (0.679)
lngdppc_i	0.713 (0.962)	-1.227*** (0.296)	-0.020 (0.489)	-2.271*** (0.376)
lngdppc_o	0.532 (0.699)	-0.978*** (0.246)	0.778 (0.517)	-1.046*** (0.405)
lngdp_i	0.739*** (0.272)	0.890*** (0.089)	-2.184*** (0.425)	1.553*** (0.235)
lngdp_o	0.201 (0.177)	0.310*** (0.092)	-0.204 (0.303)	0.626*** (0.207)
techdist_s	-2.058** (0.941)	-4.404*** (0.534)	-5.256*** (1.344)	-3.584*** (0.995)
techdist_cs	-0.084 (0.981)	-0.192 (0.424)	0.339 (0.721)	-0.398 (0.435)
techdist_c	-0.811 (1.113)	-5.380*** (0.568)	-2.301** (1.069)	-2.804*** (0.493)
lndist	0.051 (0.150)	-0.437*** (0.041)	-0.268*** (0.098)	-0.136*** (0.051)
contig	0.886*** (0.256)	-0.332*** (0.109)	0.257 (0.201)	0.635*** (0.145)
comlang_off	0.328 (0.225)	0.764*** (0.104)	0.573** (0.247)	0.740*** (0.094)
colony	-0.730* (0.401)	-0.271** (0.106)	-0.780*** (0.202)	-0.260** (0.129)
c.pair	3.148*** (0.422)	1.126*** (0.143)	2.543*** (0.366)	2.453*** (0.199)
s.pair	-0.113 (0.830)	-1.802*** (0.470)	-1.693* (0.881)	-0.958 (0.622)
cs.pair	0.227 (0.353)	0.344 (0.343)	0.293 (0.638)	0.084 (0.326)
Observations	16,404	19,284	22,540	26,428
Log-likelihood	-94056	-22139	-83920	-83439
Wald chi2	5117	3753	1712	8119

Cluster robust standard errors in parentheses, constants are suppressed.
*** p<0.01, ** p<0.05, * p<0.1

(a) Selected low-tech input industries

VARIABLES	(1)	(2)	(3)	(4)
l.lnI_i	0.254 (0.694)	0.365* (0.220)	0.594 (1.172)	0.418 (0.344)
l.lnI_o	0.054 (0.074)	0.049 (0.099)	0.543* (0.318)	0.114 (0.098)
l.lnE_i	-0.002 (0.006)	-0.008** (0.004)	0.020*** (0.006)	0.006 (0.010)
l.lnE_o	0.008 (0.008)	0.001 (0.004)	0.010* (0.006)	-0.000 (0.009)
rdint_i	-0.055*** (0.015)	0.009 (0.029)	0.034*** (0.010)	0.002 (0.013)
rdint_o	-0.006 (0.008)	-0.031*** (0.008)	0.023* (0.014)	-0.033*** (0.012)
invint_i	-0.012* (0.007)	0.008 (0.015)	-0.004 (0.017)	-0.006 (0.007)
invint_o	0.005** (0.003)	0.001 (0.006)	-0.017* (0.009)	0.005 (0.006)
lnempn_i	0.992 (0.994)	1.400*** (0.337)	-0.783 (1.807)	-1.130 (0.870)
lnempn_o	0.329 (0.236)	0.220 (0.276)	-0.059 (0.391)	0.241 (0.320)
researchers_i	-2.073 (1.752)	2.814*** (0.551)	2.768 (2.887)	4.318*** (1.328)
researchers_o	2.413*** (0.798)	3.358*** (0.579)	1.573 (1.224)	2.062 (1.270)
lngdppc_i	1.295 (0.866)	0.681 (0.611)	16.518 (11.684)	-3.131*** (0.928)
lngdppc_o	0.304 (0.836)	-0.660 (0.585)	6.747** (3.140)	-0.621 (0.517)
lngdp_i	-0.634 (0.460)	-1.162*** (0.364)	-16.322 (11.516)	1.618*** (0.596)
lngdp_o	-0.312 (0.530)	0.122 (0.416)	-5.892* (3.250)	0.537 (0.331)
techdist_s	0.885 (1.338)	-2.307* (1.205)	-1.901 (1.851)	-1.819 (1.574)
techdist_cs	-2.213*** (0.683)	-2.714*** (0.611)	-0.546 (0.833)	-1.064 (0.957)
techdist_c	-2.808*** (0.820)	-1.976** (0.894)	-5.374*** (1.895)	-2.196** (1.067)
lndist	0.373 (0.262)	0.334 (0.271)	11.171 (7.598)	-0.071 (0.177)
contig	1.015* (0.561)	0.928 (0.627)	7.573 (5.516)	0.779** (0.367)
comlang_off	0.336 (0.303)	1.001*** (0.186)	9.668 (7.073)	0.537*** (0.168)
colony	0.841 (0.686)	0.570 (0.467)	-4.648 (5.968)	-0.318 (0.221)
c.pair	3.463*** (0.754)	3.461*** (0.728)	24.324** (12.167)	2.517*** (0.389)
s.pair	2.142*** (0.668)	-0.945* (0.544)	-0.619 (2.062)	-0.238 (1.251)
cs.pair	0.052 (0.486)	-0.151 (0.388)	0.414 (1.054)	0.195 (0.434)
Observations	26,100	29,273	27,675	21,577
Log-likelihood	-350988	-176745	-519514	-144477
Wald chi2	9930	11801	7120	6108

Cluster robust standard errors in parentheses, constants are suppressed.
*** p<0.01, ** p<0.05, * p<0.1

(b) High-tech input industries

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

The column numbers refer to the following input industries: (a)(1) Agriculture, Hunting, Forestry and Fishing (2) Wood and Products of Wood and Cork (3) Pulp, Paper, Printing and Publishing (4) Construction; (b)(1) Chemicals and Chemical Products (2) Machinery, nec (3) Electrical and Optical Equipment (4) Transport Equipment.

VARIABLES	(1)	(2)	(3)	(4)
l.lnLi	-0.032 (0.048)	-0.078*** (0.026)	0.279*** (0.099)	-0.120*** (0.046)
l.lnLo	0.090* (0.054)	0.119*** (0.031)	0.265*** (0.088)	0.069 (0.043)
l.lnE_high_i	-0.254 (0.275)	0.043 (0.228)	1.070*** (0.201)	0.101*** (0.039)
l.lnE_high_ratio_i	-1.974 (2.502)	0.364 (0.897)	13.502*** (2.994)	3.657*** (1.454)
l.lnE_high_o	0.036 (0.023)	0.112*** (0.019)	0.046 (0.051)	0.010 (0.026)
l.lnE_high_ratio_o	1.029 (1.076)	3.311*** (0.703)	0.930 (1.972)	0.234 (0.960)
rdint_i	0.339*** (0.148)	0.136 (0.091)	-0.039 (0.089)	-0.173 (0.108)
rdint_o	-0.017 (0.011)	-0.018* (0.011)	0.008 (0.013)	-0.015 (0.010)
invint_i	-0.009 (0.013)	0.001 (0.006)	-0.022* (0.013)	0.026 (0.027)
invint_o	0.006 (0.005)	0.003 (0.005)	0.007 (0.007)	0.006 (0.004)
lnempn_i	-0.283 (0.336)	0.071 (0.104)	2.675*** (0.369)	-0.513** (0.229)
lnempn_o	0.510*** (0.179)	0.347*** (0.078)	0.635*** (0.178)	0.188 (0.194)
researchers_i	-2.040 (1.317)	3.672*** (1.377)	3.653*** (1.102)	4.520*** (0.652)
researchers_o	0.489 (0.849)	2.435*** (0.394)	2.223*** (0.964)	2.234*** (0.697)
lngdppc_i	0.753 (0.964)	-1.274*** (0.322)	-0.048 (0.490)	-2.297*** (0.370)
lngdppc_o	0.611 (0.716)	-0.972*** (0.245)	0.710 (0.494)	-0.973** (0.393)
lngdp_i	0.737*** (0.277)	0.864*** (0.089)	-2.152*** (0.420)	1.580*** (0.234)
lngdp_o	0.182 (0.186)	0.306*** (0.089)	-0.075 (0.237)	0.592*** (0.198)
techdist_s	-2.129** (0.918)	-4.375*** (1.379)	-5.173*** (0.973)	-3.533*** (0.973)
techdist_cs	-0.057 (1.027)	-0.204 (0.416)	0.356 (0.758)	-0.366 (0.421)
techdist_c	-0.853 (1.170)	-5.342*** (0.535)	-2.181** (0.866)	-2.658*** (0.503)
Indist	0.069 (0.159)	-0.433*** (0.041)	-0.264*** (0.090)	-0.136*** (0.050)
contig	0.915*** (0.259)	-0.334*** (0.106)	0.255 (0.184)	0.649*** (0.142)
comlang_off	0.311 (0.229)	0.776*** (0.105)	0.565** (0.232)	0.742*** (0.092)
colony	-0.731* (0.400)	-0.282*** (0.105)	-0.809*** (0.200)	-0.256** (0.125)
c_pair	3.193*** (0.439)	1.141*** (0.141)	2.525*** (0.316)	2.475*** (0.196)
s_pair	-0.129 (0.796)	-2.014*** (0.471)	-1.475 (0.904)	-0.998* (0.605)
cs_pair	0.234 (0.337)	0.261 (0.322)	0.340 (0.625)	0.086 (0.322)
Observations	16,404	19,284	22,540	26,428
Log-likelihood	-93960	-22077	-82743	-83144
Wald chi2	5194	3971	1959	8708

Cluster robust standard errors in parentheses, constants are suppressed.
*** p<0.01, ** p<0.05, * p<0.1

(a) Selected low-tech input industries

VARIABLES	(1)	(2)	(3)	(4)
l.lnLi	0.290 (0.695)	0.350* (0.199)	0.716 (1.179)	0.537 (0.370)
l.lnLo	0.051 (0.076)	0.087 (0.053)	0.549* (0.312)	0.057 (0.130)
l.lnE_high_i	-0.009 (0.011)	0.110*** (0.033)	0.062** (0.029)	0.006 (0.012)
l.lnE_high_ratio_i	-0.394 (1.287)	4.662*** (1.131)	1.650 (1.131)	-0.051 (0.215)
l.lnE_high_o	0.012 (0.014)	-0.047*** (0.012)	-0.002 (0.018)	0.070*** (0.022)
l.lnE_high_ratio_o	0.180 (0.502)	-1.940*** (0.408)	-0.560 (0.795)	2.671*** (0.782)
rdint_i	-0.055*** (0.015)	0.007 (0.029)	0.031*** (0.010)	0.008 (0.013)
rdint_o	-0.006 (0.009)	-0.026*** (0.007)	0.024* (0.014)	-0.040*** (0.013)
invint_i	-0.012* (0.007)	0.014 (0.013)	-0.004 (0.017)	-0.006 (0.007)
invint_o	0.005* (0.003)	0.003 (0.005)	-0.016** (0.008)	0.005 (0.007)
lnempn_i	0.954 (0.993)	1.316*** (0.287)	0.954 (1.917)	-1.343 (0.900)
lnempn_o	0.356 (0.242)	0.027 (0.249)	-0.108 (0.381)	0.388 (0.363)
researchers_i	-2.012 (1.726)	2.757*** (0.531)	2.353 (1.308)	3.996*** (1.300)
researchers_o	2.402*** (0.792)	3.216*** (0.567)	1.398 (1.219)	2.341* (1.352)
lngdppc_i	1.207 (0.871)	0.445 (0.536)	21.133 (13.478)	-3.076*** (0.902)
lngdppc_o	0.280 (0.828)	-1.042*** (0.378)	6.743** (3.335)	-0.673 (0.515)
lngdp_i	-0.632 (0.457)	-0.955*** (0.266)	-20.578 (13.077)	1.592*** (0.595)
lngdp_o	-0.310 (0.513)	0.458* (0.234)	-5.939* (3.431)	0.414 (0.365)
techdist_s	0.305 (1.329)	-3.332*** (1.229)	-0.758 (1.793)	-0.950 (1.545)
techdist_cs	-2.212*** (0.678)	-2.390*** (0.617)	-0.472 (0.805)	-0.968 (0.796)
techdist_c	-2.779*** (0.811)	-2.017*** (0.885)	-5.460*** (1.977)	-2.085* (1.094)
Indist	0.361 (0.252)	0.184 (0.132)	13.163 (8.149)	-0.031 (0.184)
contig	1.005* (0.547)	0.665*** (0.324)	9.806* (5.818)	0.857*** (0.423)
comlang_off	0.352 (0.293)	0.998*** (0.151)	12.492 (8.476)	0.539*** (0.187)
colony	0.826 (0.675)	0.357 (0.267)	-4.199 (5.520)	-0.261 (0.236)
c_pair	3.441*** (0.716)	3.149*** (0.290)	28.141** (13.872)	2.612*** (0.430)
s_pair	2.135*** (0.674)	-1.281** (0.553)	0.249 (1.821)	0.769 (1.336)
cs_pair	0.046 (0.478)	-0.122 (0.346)	0.359 (1.143)	0.157 (0.482)
Observations	26,100	29,273	27,675	21,577
Log-likelihood	-350838	-173438	-515170	-143399
Wald chi2	10421	9507	7665	6620

Cluster robust standard errors in parentheses, constants are suppressed.
*** p<0.01, ** p<0.05, * p<0.1

(b) High-tech input industries

Table A.8: Poisson models for different input 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

The column numbers refer to the following input industries: (a)(1) Agriculture, Hunting, Forestry and Fishing (2) Wood and Products of Wood and Cork (3) Pulp, Paper, Printing and Publishing (4) Construction; (b)(1) Chemicals and Chemical Products (2) Machinery, nec (3) Electrical and Optical Equipment (4) Transport Equipment.

VARIABLES	(1)	(2)	(3)	(4)
l.lnLi	-0.027 (0.044)	-0.091*** (0.031)	0.319*** (0.114)	-0.116*** (0.042)
l.lnLo	0.088** (0.049)	0.127*** (0.039)	0.289*** (0.096)	0.076* (0.042)
l.lnE_high_top_i	0.065 (0.268)	-0.010 (0.199)	0.781*** (0.207)	0.007* (0.004)
l.lnE_high_top_ratio_i	2.864** (1.241)	0.015 (0.319)	1.244* (0.728)	0.216 (0.227)
l.lnE_high_top_o	0.012* (0.006)	0.025*** (0.004)	0.022*** (0.007)	0.005 (0.004)
l.lnE_high_top_ratio_o	-0.140 (0.179)	0.083 (0.099)	0.041 (0.303)	0.141 (0.089)
rdint_i	0.233** (0.125)	0.148 (0.092)	-0.035 (0.089)	-0.164 (0.119)
rdint_o	-0.014 (0.011)	-0.013 (0.012)	0.005 (0.013)	-0.015 (0.011)
invint_i	-0.008 (0.013)	0.002 (0.006)	-0.022 (0.014)	0.023 (0.026)
invint_o	0.006 (0.005)	0.004 (0.005)	0.008 (0.006)	0.006 (0.004)
lnempn_i	-0.324 (0.312)	0.061 (1.103)	2.615*** (0.363)	-0.451** (0.223)
lnempn_o	0.495*** (0.157)	0.321*** (0.079)	0.743*** (0.246)	0.174 (0.180)
researchers_i	-2.139** (1.281)	3.832*** (0.381)	3.512*** (1.159)	4.400*** (0.641)
researchers_o	0.612 (0.838)	2.393*** (0.424)	2.337*** (1.035)	2.355*** (0.687)
lngdppc_i	0.557 (0.993)	-1.236*** (0.300)	-0.046 (0.493)	-2.138*** (0.332)
lngdppc_o	0.465 (0.686)	-0.978** (0.245)	0.817 (0.520)	-0.967*** (0.355)
lngdp_i	0.752*** (0.277)	0.888*** (0.089)	-2.137*** (0.426)	1.505*** (0.227)
lngdp_o	0.219 (0.156)	0.312*** (0.092)	-0.217 (0.308)	0.601*** (0.187)
techdist_s	-2.051** (0.909)	-4.395*** (0.536)	-5.239*** (1.390)	-3.530*** (0.946)
techdist_cs	-0.085 (0.960)	-0.190 (0.424)	0.518 (0.831)	-0.408 (0.432)
techdist_c	-0.807 (1.105)	-5.374*** (0.564)	-2.380*** (1.144)	-2.796*** (0.488)
lndist	0.040 (0.151)	-0.438*** (0.041)	-0.263*** (0.099)	-0.144*** (0.045)
contig	0.850*** (0.250)	-0.334*** (0.110)	0.265 (0.204)	0.599*** (0.120)
comlang_off	0.360* (0.215)	0.764*** (0.104)	0.571** (0.248)	0.740*** (0.087)
colony	-0.754** (0.383)	-0.272** (0.106)	-0.797*** (0.206)	-0.263** (0.117)
c-pair	3.148*** (0.436)	1.125*** (0.144)	2.561*** (0.380)	2.422*** (0.175)
s-pair	-0.088 (0.788)	-1.810*** (0.472)	-1.575* (0.915)	-0.992* (0.597)
cs-pair	0.223 (0.337)	0.342 (0.342)	0.333 (0.653)	0.080 (0.313)
Observations	16,404	19,284	22,540	26,428
Log-likelihood	-93733	-22139	-83849	-83224
Wald chi2	5507	3801	1828	9392

Cluster robust standard errors in parentheses, constants are suppressed.
*** p<0.01, ** p<0.05, * p<0.1

(a) Selected low-tech input industries

VARIABLES	(1)	(2)	(3)	(4)
l.lnLi	0.255 (0.692)	0.391** (0.184)	0.233 (1.071)	0.450 (0.354)
l.lnLo	0.051 (0.073)	0.096* (0.058)	0.613* (0.371)	0.088 (0.108)
l.lnE_high_top_i	-0.002 (0.006)	-0.005 (0.007)	0.017* (0.010)	0.009 (0.010)
l.lnE_high_top_ratio_i	0.014 (0.435)	0.213 (0.155)	-0.072 (0.155)	0.179 (0.127)
l.lnE_high_top_o	0.009 (0.008)	-0.008* (0.005)	0.024** (0.010)	0.001 (0.009)
l.lnE_high_top_ratio_o	0.012 (0.017)	-0.477*** (0.138)	-0.359 (0.230)	0.106* (0.065)
rdint_i	-0.055*** (0.015)	-0.000 (0.034)	0.033*** (0.009)	0.004 (0.013)
rdint_o	-0.006 (0.008)	-0.030*** (0.009)	0.022* (0.012)	-0.035*** (0.012)
invint_i	-0.012* (0.007)	0.013 (0.013)	-0.009 (0.016)	-0.006 (0.007)
invint_o	0.005** (0.003)	0.004 (0.005)	-0.012 (0.007)	0.005 (0.006)
lnempn_i	0.994 (0.994)	1.371*** (0.290)	0.273 (1.454)	-1.192 (0.884)
lnempn_o	0.326 (0.235)	0.073 (0.263)	-0.257 (0.453)	0.274 (0.325)
researchers_i	-2.078 (1.754)	2.713*** (0.548)	3.988* (2.418)	4.144*** (1.302)
researchers_o	2.412*** (0.797)	3.248*** (0.564)	2.091* (1.177)	2.088* (1.254)
lngdppc_i	1.307 (0.865)	0.701 (0.558)	6.631 (9.494)	-3.066*** (0.918)
lngdppc_o	0.311 (0.836)	-1.038*** (0.403)	1.401 (2.273)	-0.645 (0.518)
lngdp_i	-0.639 (0.459)	-1.080*** (0.297)	-7.300 (9.478)	1.619*** (0.598)
lngdp_o	-0.315 (0.534)	0.378 (0.279)	-1.024 (1.841)	0.522 (0.334)
techdist_s	0.868 (1.344)	-3.519*** (1.198)	-0.291 (1.768)	-1.812 (1.554)
techdist_cs	-2.227*** (0.684)	-2.430*** (0.683)	-0.905 (0.691)	-1.030 (0.924)
techdist_c	-2.803*** (0.822)	-2.277** (1.044)	-4.656*** (1.502)	-2.224** (1.052)
lndist	0.373 (0.266)	0.237 (0.168)	5.759 (6.611)	-0.068 (0.174)
contig	1.018* (0.565)	0.715* (0.398)	9.040 (8.407)	0.771** (0.362)
comlang_off	0.329 (0.305)	1.031*** (0.173)	2.332 (4.385)	0.564*** (0.162)
colony	0.846 (0.690)	0.378 (0.313)	-1.305 (4.952)	-0.299 (2.211)
c-pair	3.461*** (0.770)	3.245*** (0.368)	12.560* (7.453)	2.522*** (0.392)
s-pair	2.160*** (0.661)	-1.476*** (0.549)	-3.676 (3.461)	-0.080 (1.225)
cs-pair	0.060 (0.490)	-0.137 (0.361)	-1.873 (2.543)	0.182 (0.445)
Observations	26,100	29,273	27,675	21,577
Log-likelihood	-350902	-174491	-501945	-144203
Wald chi2	10118	9610	5613	6646

Cluster robust standard errors in parentheses, constants are suppressed.
*** p<0.01, ** p<0.05, * p<0.1

(b) High-tech input industries

Table A.9: Poisson models for different input industries with external 'top' high-tech and low-tech R&D stocks, dependent variable: number of forward citations that input sector-country receives from output sector-country

The column numbers refer to the following input industries: (a)(1) Agriculture, Hunting, Forestry and Fishing (2) Wood and Products of Wood and Cork (3) Pulp, Paper, Printing and Publishing (4) Construction; (b)(1) Chemicals and Chemical Products (2) Machinery, nec (3) Electrical and Optical Equipment (4) Transport Equipment.

B Appendix

B.1 Derivation of the empirical model

Let

$$Q_{ci,si,t} = I_{ci,si,t-1}^{\alpha_1} E_{ci,si,t-1}^{\alpha_2} e^{v_{ci}} e^{v_{si}} e^{v_t} \quad (\text{B.1})$$

a log-linear production function where $Q_{ci,si,t}$ is technological output ('innovations') in country ci , industry si in year t . $I_{ci,si,t}$ is the knowledge stock that is accumulated 'own' knowledge that accrues to the focal sector-country, $E_{ci,si,t}$ is potentially accessible knowledge that is accumulated in other sector-countries (external knowledge), $e^{v_{ci}}$, $e^{v_{si}}$, and e^{v_t} capture country, industry and time specific effects. We assume that some fraction of $Q_{ci,si,t}$ is patented ($1/\lambda_{ci,si,t}$) and that the number of new patents is given by

$$P_{ci,si,t} = 1/\lambda_{ci,si,t} Q_{ci,si,t} = 1/\lambda_{ci,si,t} I_{ci,si,t-1}^{\alpha_1} E_{ci,si,t-1}^{\alpha_2} e^{v_{ci}} e^{v_{si}} e^{v_t} \quad (\text{B.2})$$

A fraction of the patents in ci, si is cited by co, so and $C_{ci,si,co,so,t}$ is the number of citations that the input sector-country ci, si receives from co, so . Following Peri (2005), we assume that citations are a noisy indicator of actual outflows $\Phi_{ci,si,co,so,t}$ and include an error term:

$$C_{ci,si,co,so,t} = \Phi_{ci,si,co,so,t} e^{\epsilon_{ci,si,co,so,t}} \quad (\text{B.3})$$

The number of actual knowledge flows that goes from ci, si to co, so relative to the number of innovations in ci, si times the number of innovations in co, so is given by

$$\theta_{ci,si,co,so,t} = \frac{\Phi_{ci,si,co,so,t}}{Q_{ci,si,t} Q_{co,so,t}} = \frac{C_{ci,si,co,so,t}}{\lambda_{ci,si,t} P_{ci,si,t} \lambda_{co,so,t} P_{co,so,t} e^{\epsilon_{ci,si,co,so,t}}} \quad (\text{B.4})$$

if we re-arrange both the first equality of (B.2) and (B.3) and insert them afterwards. Again following Peri, the relative intensity of knowledge flows between 'sending' sector-countries and 'receiving' sector-countries can be also written as an exponential function dependent on a host of geographic and technological variables:

$$\theta_{ci,si,co,so,t} = \exp(\mathbf{x}'_{ci,si,co,so,t}\boldsymbol{\beta}) \quad (\text{B.5})$$

Combining (B.4) and (B.5) and after re-arranging, $C_{ci,si,co,so,t}$ can be written as exponential function of geographic and technological variables $\mathbf{x}'_{ci,si,co,so,t}$ and patents in ci , si and co , so :

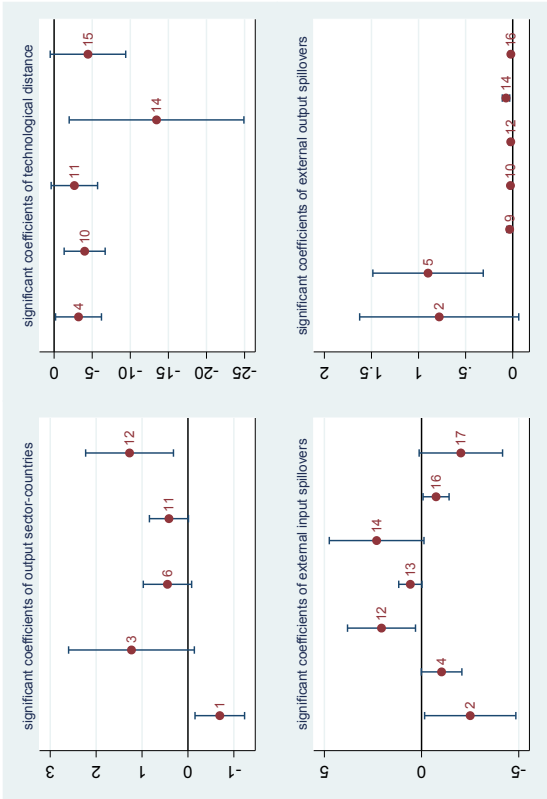
$$C_{ci,si,co,so,t} = \exp(\mathbf{x}'_{ci,si,co,so,t}\boldsymbol{\beta} + \ln P_{ci,si,t} + \ln P_{co,so,t} + \ln \lambda_{ci,si,t} + \ln \lambda_{co,so,t} + \epsilon_{ci,si,co,so,t}) \quad (\text{B.6})$$

After inserting (B.2), we receive a function that depends on input and output knowledge stocks, external spillovers, input and output specific effects, time effects, an error term and additional variables of interest $\mathbf{x}'_{ci,si,co,so,t}$:

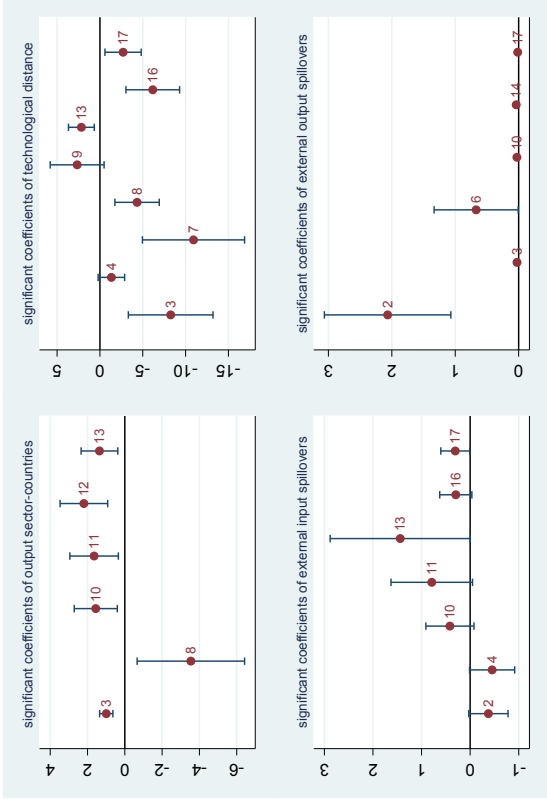
$$C_{ci,si,co,so,t} = \exp(\mathbf{x}'_{ci,si,co,so,t}\boldsymbol{\beta} + \alpha_{1i}\ln I_{ci,si,t-1} + \alpha_{1o}\ln I_{co,so,t-1} + \alpha_{2i}\ln E_{ci,si,t-1} + \alpha_{2o}\ln E_{co,so,t-1} + v_{ci} + v_{co} + v_{si} + v_{so} + v_t + \xi_{ci,si,co,so,t}) \quad (\text{B.7})$$

B.2 Further tables & figures

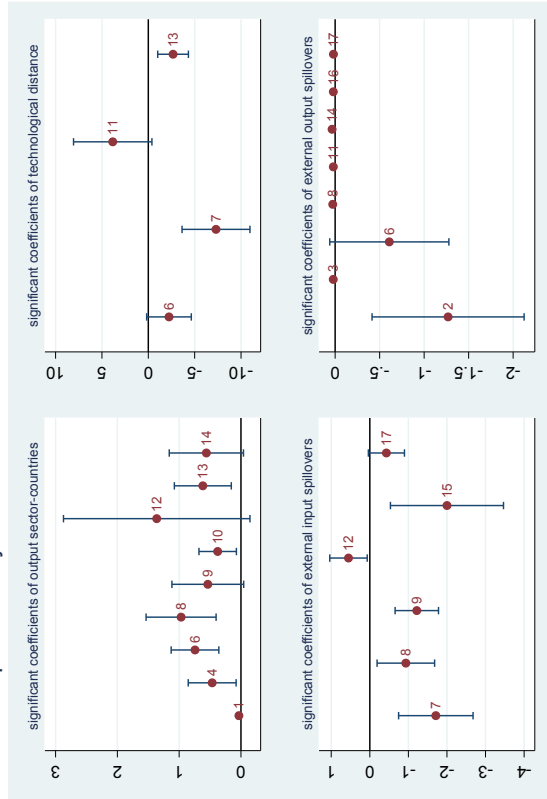
Input industry: Agriculture, Hunting, Forestry and Fishing



Input industry: Pulp, Paper, Printing and Publishing



Input industry: Wood and Products of Wood and Cork



Input industry: Construction

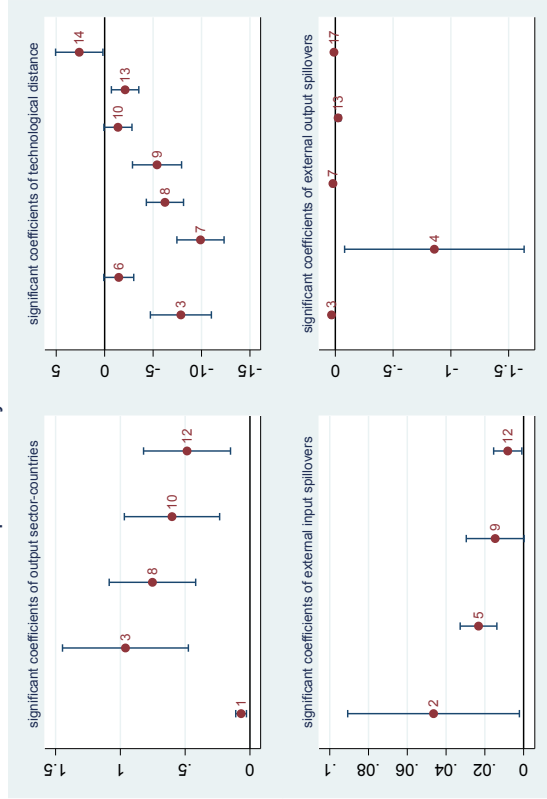
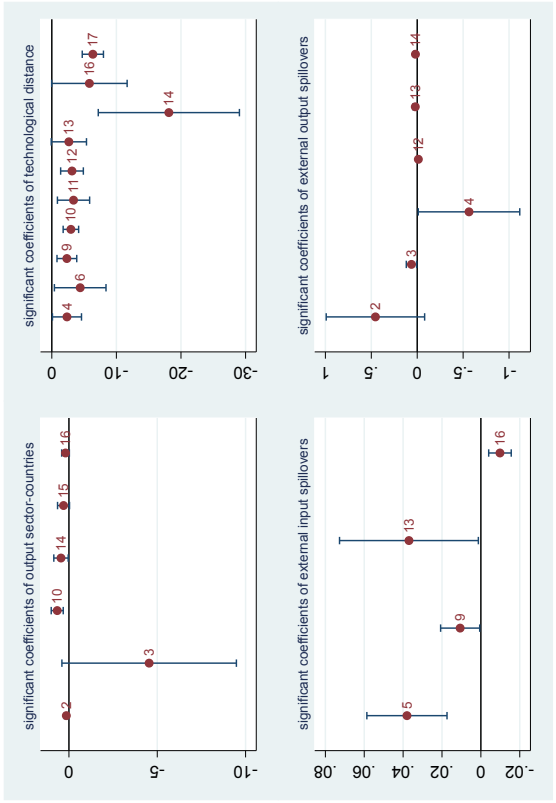


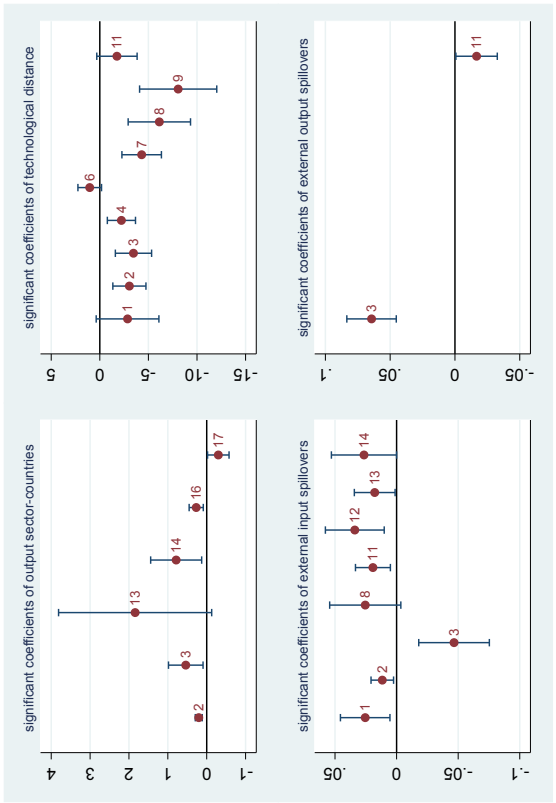
Figure 1: Significant coefficients and 95% confidence intervals for selected low-tech input industries

The numbers in the diagrams refer to the following output 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.

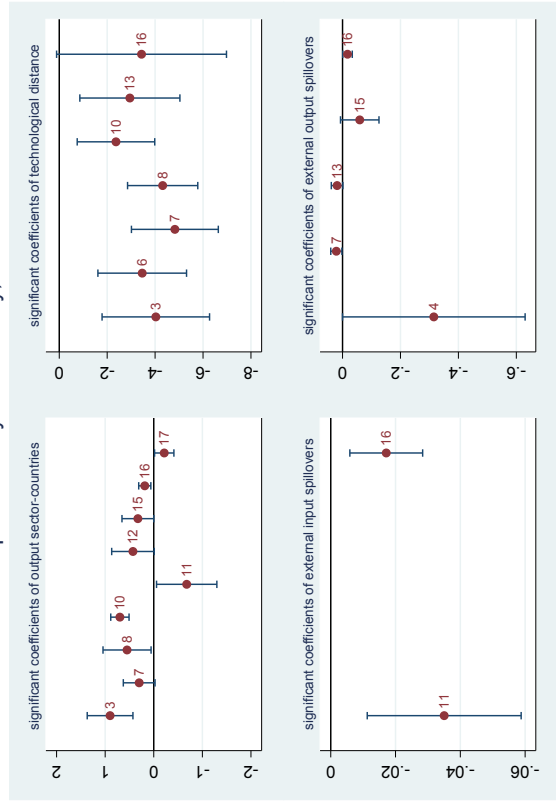
Input industry: Chemicals and Chemical Products



Input industry: Electrical and Optical Equipment



Input industry: Machinery, nec



Input industry: Transport Equipment

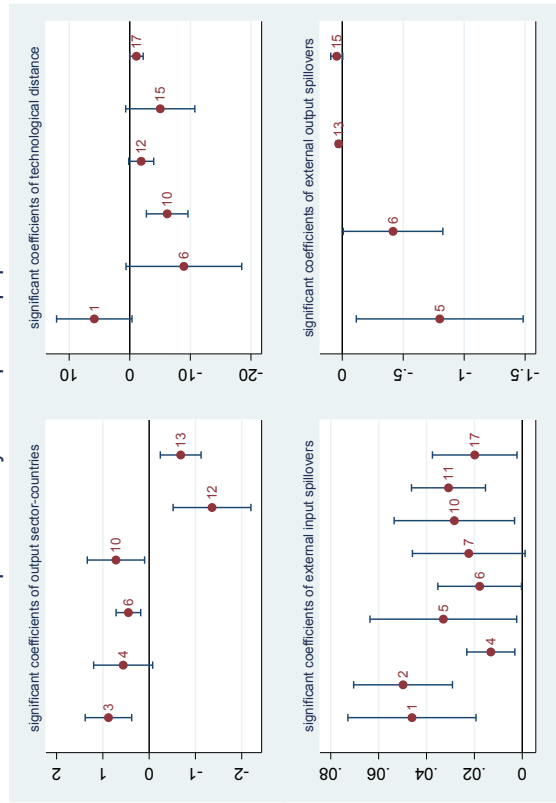


Figure 2: Significant coefficients and 95% confidence intervals for high-tech input industries

The numbers in the diagrams refer to the following output 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.

Table B.1: Logit models, dependent variable: Incidence of forward citations between input sector-country and output sector-country

VARIABLES	(1)	(2)	(3)
	Logit fw_citation_d	Logit fw_citation_d	Logit fw_citation_d
l.lnI_i	0.004* (0.002)	0.004* (0.002)	0.004* (0.002)
l.lnI_o	0.013*** (0.002)	0.013*** (0.002)	0.013*** (0.002)
l.lnE_i	-0.006*** (0.002)		
l.lnE_o	0.010*** (0.002)		
l.lnE_high_i		-0.004** (0.002)	
l.lnE_high_ratio_i		0.068*** (0.024)	
l.lnE_high_o		0.013*** (0.002)	
l.lnE_high_ratio_o		0.097*** (0.021)	
l.lnE_high_top_i			-0.006*** (0.002)
l.lnE_high_top_ratio_i			-0.010** (0.005)
l.lnE_high_top_o			0.011*** (0.002)
l.lnE_high_top_ratio_o			0.039*** (0.005)
rdint_i	0.017*** (0.001)	0.017*** (0.001)	0.017*** (0.001)
rdint_o	0.013*** (0.001)	0.013*** (0.001)	0.013*** (0.001)
invint_i	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
invint_o	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
lnempn_i	0.043*** (0.011)	0.043*** (0.011)	0.042*** (0.011)
lnempn_o	0.011 (0.011)	0.011 (0.011)	0.012 (0.011)
researchers_i	1.182*** (0.142)	1.179*** (0.142)	1.182*** (0.142)
researchers_o	0.339** (0.149)	0.335** (0.149)	0.325** (0.149)
lngdppc_i	-4.884*** (0.267)	-4.862*** (0.267)	-4.894*** (0.267)
lngdppc_o	-2.163*** (0.268)	-2.134*** (0.268)	-2.111*** (0.268)
lngdp_i	3.257*** (0.250)	3.236*** (0.250)	3.263*** (0.250)
lngdp_o	2.095*** (0.254)	2.067*** (0.254)	2.053*** (0.254)
techdist_s	-1.342*** (0.044)	-1.344*** (0.044)	-1.372*** (0.044)
techdist_cs	-0.334*** (0.039)	-0.331*** (0.039)	-0.320*** (0.039)
techdist_c	-1.112*** (0.062)	-1.115*** (0.062)	-1.116*** (0.062)
lndist	-0.064*** (0.017)	-0.064*** (0.017)	-0.064*** (0.017)
contig	0.311*** (0.026)	0.311*** (0.026)	0.311*** (0.026)
comlang_off	0.365*** (0.026)	0.365*** (0.026)	0.365*** (0.026)
colony	-0.377*** (0.030)	-0.377*** (0.030)	-0.377*** (0.030)
c_pair	2.981*** (0.062)	2.981*** (0.062)	2.982*** (0.062)
s_pair	-0.387*** (0.032)	-0.385*** (0.032)	-0.396*** (0.032)
cs_pair	-0.496** (0.210)	-0.495** (0.210)	-0.493** (0.210)
Observations	787,260	787,260	787,260
Log-likelihood	-326639	-326627	-326588
Wald chi2	132218	132285	132304

Cluster robust standard errors in parentheses,
the constant is suppressed
*** p<0.01, ** p<0.05, * p<0.1

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