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Beyond Trading: Knowledge Spillovers and learning-by-exporting in Global Value Chains*

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Abstract

Does exporting intermediate goods induce learning from importers? In this paper, we examine to what extent learning from German industries can be explained by knowledge spillovers, channeled through the export of intermediate goods. Our study is based on a sample of 27 German trade partners in 14 manufacturing industries for the period 2004 to 2016. Using data on patent citations and trading in intermediate goods, we find support for the widely known "learning-by-exporting" hypothesis. Our analyses reveal that citations to German patents are positively related to exported intermediate goods weighted by German R&D expenditure. The relationship between these spillovers and learning seems to be particularly strong in certain industries. We also show that the level of absorptive capacity of the exporting trade partner, as measured by the number of researchers involved in R&D activities, plays a role in mediating these spillovers.

Keywords: GVC, trade, intermediate goods, learning-by-exporting, knowledge spillovers
JEL classification: F14, O14, O32, O33

1 Introduction

In addition to being a central platform for trading, Global Value Chains (GVCs) evolve as a potential mediating platform for knowledge spillovers and technology transfer. Due to the different forms of interaction and reduced communication costs, the transmission of ideas across countries and industries has become possible among trading partners along sliced stages of production embedded within GVCs (Gehl Sampath & Vallejo, 2018; Gereffi, 1999; Morrison et al., 2008; Timmer et al., 2014). Moreover, transnational cooperation along GVCs is seen as an important source of knowledge spillovers, especially in the absence of strong foreign direct investment (FDI) that could foster innovation within countries (Belderbos et al., 2016; Brach & Kappel, 2009; Pietrobelli & Rabellotti, 2011).

The variety of knowledge spillover transmission channels has been widely studied and acknowledged. In addition to labor mobility, FDI, and cooperation in research, several empirical works confirm that trade is an important source of international knowledge diffusion, whether represented in R&D spillovers

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or patenting activity (Belderbos & Mohnen, 2020; Perri et al., 2017). Trade in general has been suggested as a significant channel of knowledge spillovers in the neoclassical productivity literature, where trading can positively affect a country's own productivity by facilitating knowledge flows from trade partners (Aghion & Howirrt, 1992; Grossman & Helpman, 1991; Romer, 1990). On the empirical side, early evidence by Coe and Helpman (1995) shows a positive effect of international knowledge spillovers on Total Factor Productivity (TFP) for trading partners of G7 economies, channeled through imports from G7 economies. By combining trade and patent data, Verspagen (1997) finds that imports indirectly mediate R&D spillovers. Studies by Keller (2010), Piermartini and Rubínová (2021), Tajoli and Felice (2018), and Xu and Wang (1999) provide strong evidence for the positive role of trading in capital goods and imports on knowledge and technology transfer and innovation performance. Empirical evidence has demonstrated that R&D knowledge generated in developed countries can spill over to other countries through trade channels, as shown by numerous studies (Falvey et al., 2002, 2004; Keller, 1998). It has also been shown that technological knowledge embodied in imports can lead to higher domestic productivity, with imports serving as a key channel for knowledge diffusion (Nishioka & Ripoll, 2012).

With the mentioned literature in mind, the nature of the relationship between knowledge spillovers and trade leaves open questions on the patterns of knowledge flows that can go both ways (Belderbos & Mohnen, 2020). For example, countries involved in trade could improve their productivity by absorbing knowledge from their trade partners through imported goods. Additionally, by exporting to highly innovative trading partners, countries could learn from their customers and improve their innovation performance to meet their requirements (Piermartini & Rubínová, 2021). Although the relevant literature has focused mainly on knowledge diffusion via imports, there is little evidence on the possible effects of exporting on knowledge spillovers and learning. This "learning-by-exporting" hypothesis, which states that countries become more productive and innovative as a result of exporting to highly advanced countries, remains largely unexplored in the empirical literature (Blalock & Gertler, 2004; Martins & Yang, 2009). The argument is that sophisticated demand from technologically advanced customers can be a source of "backward spillovers", however, the validity of this assumption has received little attention (Belderbos & Mohnen, 2020). Given the increasing quality requirements of technologically advanced economies for producing final goods, the demand for valuable intermediate goods arises. Consequently, intermediate goods, in particular, can be an important mechanism for learning and innovation rather than trade in general (Tajoli & Felice, 2018; Xu & Wang, 1999).

In this paper, we raise the general question of to what extent learning can be explained by the value or intensity of exported intermediate goods. We focus on Germany as the knowledge-sourcing (importing) country and its trade partners as knowledge-receiving countries that export intermediate goods to Germany. We measure learning by patent citations by the exporting industry-country to German patents belonging to the German "customer" industries. We construct a spillover measure as the share of exported intermediate goods by an industry-country weighted by German R&D expenditure. Exported intermediate goods, as a proxy for upstream value chain linkages, is the spillover channel while German R&D is the knowledge pool. In this way, we draw attention to potential knowledge spillovers that flow from German customers to foreign suppliers. The emphasis is put on Germany, given its strong base in R&D as well as its centrality in GVCs as a main demand and supply hub (World Trade Organization, 2019). Also, knowledge flows may be larger when trading with a knowledge-sourcing country (i.e., Germany) which is positioned at the technological frontier in certain industries (Belderbos & Mohnen, 2020).

To test the learning-by-exporting hypothesis, we set up a panel for the period 2004 to 2016 including data on patent citations, R&D expenditure, the value of exported intermediate goods from 27 trading partners of Germany, and FDI flows. The analysis is carried out at the industry-country level for 14 manufacturing industries in 27 countries that export intermediate goods to Germany. Using an IPC-industry concordance (Neuhäusler et al., 2019), we construct patent citation links at the industry-country level as a measure of learning (Belderbos & Mohnen, 2020).

We contribute to the empirical discussion on the nexus of trade, innovation, and international knowledge diffusion in several ways. First, we aim to empirically address the gap on the knowledge spillovers from customers to suppliers, focusing on spillovers from countries at the technological frontier which are integrated in the global economy (Ambos et al., 2021). Also, the "learning-by-exporting" hypothesis has not been explored with recent data. Therefore, investigating into this transmission channel could yield new insights, especially when it is argued that sellers possibly gain from the knowledge produced by their buyers (Grossman & Helpman, 1991). Second, we use patent citations as the measure for learning and match them to industries. This approach has been used less often compared to other methods based on R&D or patents. By conducting the analysis at the industry level, we complement the more widespread firm-level studies in testing the learning-by-exporting hypothesis (Blalock & Gertler, 2004; De Loecker, 2013; Salomon & Myles Shaver, 2005).

We find that citations to German patents (our proxy for learning) are positively related to exports of intermediate goods (the spillover channel). These spillovers are particularly strong for food and beverages, chemicals and pharmaceuticals, rubber and plastics, basic metals and metal products, machinery, computers and electronics, automotive and other transport. Given that learning through trade in value chains may require a certain level of ability of trade partners to absorb external knowledge (Ambos et al., 2021), we conduct our main analysis in subsamples of trade partners categorized according to an absorptive capacity proxy. We find that trade partners with high and medium levels of absorptive capacity are those that show more learning transmitted through the share of exported intermediate goods to German industries. In running additional analyses and robustness checks, we find that the learning premium channeled through exported intermediates is higher than through total exports excluding intermediates. The learning premium from German industries persists with an alternative spillover measure based on German patenting activity and remains higher in magnitude compared to learning sourced from other countries.

The rest of the paper is structured as follows. The next section presents a brief on the literature of trade relevancy to international R&D and productivity, as well as on learning-by-exporting literature. Section 3 presents our data sources, the main variables we use in the analysis, descriptive statistics of our data and our empirical model. Our main findings are presented in section 4. The last section discusses the results and concludes.

2 Relevant Literature

2.1 International R&D Spillovers and Trade

It has been well established in the literature that trade is not only a determinant of productivity, but also an essential channel for international R&D and knowledge spillovers. This has been confirmed by theoretical work, as well as empirical evidence on the relation between technological change, knowledge flows and trade. Among others, the works of Aghion and Howirrt (1992) and Grossman and Helpman (1991) on endogenous growth and technological change suggest that a country's own productivity depends on its domestic stock of R&D and foreign R&D efforts via different transmission channels. Grossman and Helpman (1991) in particular, argue that imports as well as exports facilitate knowledge flows, as trade increases the level of interaction that facilitates knowledge exchange. This conclusion has motivated a large part of the empirical literature to focus on international trade as a potential transmission channel for knowledge spillovers and a trigger of productivity.

Coe and Helpman (1995) have been the first to provide convincing empirical evidence that trade facilitates R&D spillovers through import flows. They argue that importers improve their domestic productivity based on the technology input embodied in the imports produced by their trade partners. By using data on domestic R&D and imports for a sample of 21 OECD countries for the period 1971 to 1990, the authors show that foreign R&D stock of the trade partners can indirectly improve domestic productivity in the importing country. Coe and Helpman (1995) construct the foreign R&D stock as a weighted sum of cumulative R&D of the country trade partners, where the weights are bilateral import shares. However, the authors do not distinguish between imported final capital goods and intermediates, but rather focus on overall imports. Their estimations suggest that a one percent increase in foreign R&D stock in the trade partners increases the TFP of importing countries by 0.04%. With this result, the authors confirm the theoretical arguments developed earlier on the dependency of domestic productivity on domestic and foreign R&D. The importance of foreign R&D is even more highlighted when taking trade flows into account. Keller (1998) further investigates the findings of Coe and Helpman (1995) on trade-related spillovers. He carries out a Monte-Carlo based robustness check comparing the elasticity of domestic productivity with regard to foreign R&D with an estimated elasticity among randomly matched counterfactual trade partners. He compares the estimation results of counterfactual trade partners with real trade partners data. While Keller (1998) arrives at similar results as Coe and Helpman (1995), he suggests that estimating R&D spillovers related to trade patterns should simultaneously allow for trade unrelated international technology diffusion. The study by Keller (1998) also challenges some of the results by Coe and Helpman (1995). First, it raises concerns about the potential endogeneity of knowledge spillovers given the endogenous technological change models proposed by Aghion and Howirrt (1992) and Romer (1990). Second, the findings by Coe and Helpman (1995) disregard the importance of intermediate goods which could trigger productivity in the importing country in case these intermediates are of a higher level of quality and technology.

By mostly focusing on capital goods, Xu and Wang (1999) empirically assess the role of trading in capital goods in mediating international R&D spillovers in OECD countries. The authors focus only on capital goods, given their higher content of technology that carry forward R&D spillovers compared to non-capital goods. They follow the approach by Coe and Helpman (1995) in constructing the measure on foreign R&D, and create capital goods weighted R&D spillover and non-capital goods weighted R&D spillover measures for a sample of 21 OECD countries for the 1983 to 1990 period. Their main finding implies that importing capital goods is a significant channel for foreign R&D spillovers, where a 34% return on R&D investment in foreign countries is transmitted to importing countries via the capital goods weighted foreign R&D variable. Other possible channels of R&D spillovers, as well as possible endogeneity problems, are not controlled for. Keller (2002) builds on earlier work on R&D and trade and focuses in particular on inter-industry knowledge flows mediated by intermediate goods in eight OECD economies. By using data covering R&D spending and trading in intermediates for the period 1970 to 1991, the main finding shows strong productivity effects of foreign R&D spending on domestic R&D mediated by importing advanced intermediate goods. It is estimated that own R&D spending increases domestic productivity by 50%, while foreign technology spillovers account for 20 to 30% of the productivity increase mediated by the import of advanced intermediate goods. Falvey et al. (2002) find that the level of trade is important for facilitating North-South R&D knowledge spillovers by looking at import flows from OECD to developing countries. Using bilateral import weighting schemes, they show that a one percent increase in the knowledge stock of an OECD country is positively associated with a 0.07% increase in domestic per capita GDP growth.

While many authors have used R&D spillover proxies to study the TFP-related benefits of trade, the study by Sjöholm (1996) is among the first to use patent citations to examine the role of international trade in knowledge flows. The use of patent citations is motivated by the fact that an invention must be of high technological and commercial value, while building on existing knowledge requires a sufficient level of absorptive capacity. Sjöholm (1996) finds that total trade flows, including exports and imports, have a positive impact on the number of citations to foreign knowledge of trade partners. For example, the probability of a country citing a Swedish patent application increases with the volume of trade between the two countries. Their result is also robust to different country subsamples.

Recent evidence on trade-related knowledge spillovers corroborates these findings. Ali et al. (2016) extend the work by Coe and Helpman (1995) and consider FDI as an additional channel for R&D

spillovers. The authors estimate the impact of imports and inward FDI on domestic productivity for 20 European economies from 1995 to 2010. Ali et al. (2016) find that countries with higher quality human capital, proxied by patenting activity, benefit from absorption and transmission of knowledge spillovers channeled through imports and FDI. Overall, the productivity-enhancing effects of FDI and imports are once again confirmed. While many studies investigate the role of trade in mediating R&D spillovers on domestic TFP, Piermartini and Rubínová (2021) examine the returns of GVC participation in innovation measured by patent applications. By combining data on trade in value-added and patent data for 25 countries at the industry level for the period 2003 to 2012, the authors study how foreign R&D expenditure support domestic patenting activity through participation in GVCs. Piermartini and Rubínová (2021) find that GVC participation improves innovation performance by 5% in a sample of developed and emerging economies, while absorptive capacity strengthens spillover transmission.

2.2 The learning-by-exporting Hypothesis

As can be seen from the review above, a large part of the literature has focused on imports as a channel for knowledge spillovers, while exports have received less attention, especially at the country level.

In a two-country trade-induced learning model developed by Chuang (1998), a country with a comparative advantage in a technology diffuses its technology to the comparatively less advanced trading partner. Chuang (1998) theorizes that trade can induce learning, with imports and exports being important sources of technology spillovers. While exporting intensifies the learning-by-doing process, the intensity of learning under each trade flow depends on the type of the trading partner transmitting the spillovers (Falvey et al., 2002) and on the level of technological sophistication of the exported goods. The technology gap between trading partners and the degree of trade openness may also determine the intensity of learning. Chuang (1998) argues that in an internationally competitive market, exporting improves technology diffusion as firms gradually learn and absorb the required technology to produce higher quality products that meet the needs of their customers. Theoretical arguments such as those of Chuang (1998) and others have drawn attention to a possible learning effect transmitted by export flows, widely known as the "learning-by-exporting" hypothesis.

The first to address the learning-by-exporting hypothesis in an empirical framework was Funk (2001), who re-examines the relationship between trade and R&D spillovers with a focus on export channels. Funk (2001) argues that the role of imported intermediates may be overstated and that other transmission channels should be better understood. Funk (2001) uses the same data as Coe and Helpman (1995), but proposes a refined estimation method using first differences to avoid non-stationarity problems. He finds that bilateral import-weighted foreign R&D is statistically insignificant, while the opposite is true for export-weighted foreign R&D. Funk (2001) argues that imports should not be considered as the main and only mechanism for knowledge spillovers for several reasons. The main reason lies in the nature of the knowledge transferred through import or export channels. In his explanation, imports are a major channel for pecuniary spillovers because the price of a new intermediate input may not fully reflect its marginal product. However, such spillovers may not lead to long-term productivity effects. Pure knowledge spillovers are more likely to be transmitted through export channels. For example, the intensity of contacts accompanying exports induces customers to provide information or access to technology that leads to productivity improvements for the exporters. By showing that exporters gain knowledge from their customers, Funk (2001) makes a strong case for the learning-by-exporting effect. He concludes that the choice of weights in constructing the spillover measure is informative about the nature of the channel that facilitates knowledge spillovers and has different implications accordingly. Falvey et al. (2004) study whether exports can be a channel for R&D spillovers in 21 OECD countries for the period 1975-1990. In addition to import spillovers, their measure of export spillovers is positive and statistically significant, especially when the transferred foreign knowledge is assumed to be a public good.

The learning-by-exporting hypothesis has been tested mainly at the firm level. Blalock and Gertler (2004) study whether firms become more productive through learning-by-exporting. The authors use a panel of manufacturing firms in a developing context – namely Indonesia – for the period 1990 to 1996 and find that productivity increases by 2% to 5% following their involvement in exporting activities. The authors argue that firms can benefit more from the technical and technological expertise of their foreign customers, especially those that are technologically sophisticated. Through several empirical tests regarding the timing of firm performance, the authors confirm a learning effect rather than a self-selection of the most productive firms into export markets. Crespi et al. (2008) use firm level panel data from the UK Community Innovation Survey (CIS) for the period from 1994 to 2000 and find support for the learning-by-exporting hypothesis. They do not use a direct measure of learning but construct a variable for labor productivity growth, which is used as a proxy for learning. Specifically, the authors find that firms that have exported in the past are more likely to learn from their customers, while the opposite is not true, i.e., past productivity is not associated with learning from customers. In a similar study, De Loecker (2013) uses Slovenian firm-level data and finds positive within-firm productivity effects when firms enter international markets through exports. The author finds a productivity-enhancing effect of exports of about 4% while controlling for firm-level productivity-enhancing variables such as R&D, technology adoption and quality improvement. The observed effect appears to vary with the heterogeneous performance of firms in the sample. In a meta-analysis of about 30 studies examining the relationship between productivity and exports, mainly at the firm level, Martins and Yang (2009) find that the productivity effect of exporting is more significant for firms in developing countries than in developed countries. The authors consider the different methods used in these studies as well as the way the outcome variables are measured and the countries covered. Their results remain robust to different specifications and weighting mechanisms. Complementing the work on learning-by-exporting, Masso and Vahter (2023) study the productivity effects of the formation and termination of supply linkages between domestic firms and their foreign-owned customers in the host economy of FDI. Their analysis, based on firm transaction data, reveals that trading with multinational firms leads to a significant improvement in labor productivity at the domestic firm level, with no effect on TFP. The authors attribute this productivity increase to the continuous flow of knowledge from multinationals to domestic firms in the host economy.

Similar to the above-mentioned studies, our research question is derived from the learning-by-exporting hypothesis. However, we aim to test the validity of this hypothesis at the more aggregated industry-country level and to compare these results with existing firm-level studies. We examine the extent to which learning – proxied by citations to German patents – can be explained by exports of intermediate goods weighted by German R&D, our measure of the spillover channel. We focus only on GVC flows associated with Germany, in particular the intermediate goods exported by trading partners to German manufacturing industries for incorporation into subsequent production processes for the final good. A positive association would indicate an induced learning effect from the German industries (the buyers) to the exporting industries in the trading partners (the sellers). While the literature has largely focused on TFP and other productivity measures as the main outcome variables, we measure learning more directly through patent citations. Specifically, citations by the foreign exporting industries to any of the German importing industries, which are assumed to be the source of knowledge spillovers. With this in mind, our hypotheses to be tested are formulated as follows:

Hypothesis 1 *Exporting intermediate goods to German industries is positively associated with citing German patents.*

Hypothesis 2 *The level of absorptive capacity of an exporting trade partner plays a positive role in facilitating spillovers from Germany.*

3 Data and Methods

3.1 Data sources and variables

We combine several data sources for our analysis. Our final data include information on patent citations, trade in intermediates, business R&D expenditure, as well as FDI flows for a sample of 27 trade partners of Germany in 14 manufacturing industries during the period 2004 to 2016. We use the OECD REGPAT and citations databases (both July 2021) to identify German patents and patents cited by the trade partners. The OECD REGPAT data provides information on inventor location and the International Patent Classification (IPCs) for each patent application at the European Patent Office (EPO). To track annual exports of intermediate goods to Germany, we rely on the OECD Bilateral Trade Database by Industry and End-Use (BTDIxE). The BTDIxE data have been developed mainly to better understand the role of semi-manufactured or intermediate goods in global trade (OECD, 2017). It includes information on export and import flows disaggregated by end-user categories such as capital goods, consumption or intermediate goods and are broken down by the reporting (exporting) industry following the ISIC.4 industry classification. Trade flows are based on historical records from the UN Comtrade and the OECD International Trade by Commodity Statistics (ITCS), where products are then assigned to industries based on the Harmonized System nomenclature (HS) product classification. Furthermore, we rely on the OECD business enterprise data for R&D expenditure at the industry level for Germany and its trade partners. Finally, we add data on German FDI flows to the 27 trade partners from the OECD FDI flows data.

Dependent variable: Citation Link

Our dependent variable is the *Citation Link* at the industry-country level. It is constructed using patent and citation data from the OECD REGPAT database combined with the OECD Citations database. We restrict the patent sample to applications registered at the European Patent Office (EPO) to ensure a consistent and adequate level of patent quality and application requirements. For each patent application, we identify the geographical location based on inventor location and the technological fields (3-digit IPCs). Since patent applications can be a result of collaboration among inventors from different countries, we assign patents to the country which has an inventor share of at least 50%. By that, we are able to identify German patents and patents from Germany trade partners. We limit citations to include only cited German patents and citing patents from the 27 trade partners. By using a citation ID that links the citing patent application of the trade partner to the German cited patent application IDs, we are able to track citations from the trade partners to German patents as our indicator for knowledge flows.

As the first step in constructing our outcome variable *citation link*, we calculate the *citation weight* (CW) between the 3-digit IPC classes i (citing) and j (cited):

$$CW_{i,j} = \sum_{h} \frac{S_{h,i,j}}{\sum_i \sum_j S_{h,i,j}} \tag{1}$$

In equation 1, $CW_{i,j}$ is calculated as the sum of fractional citations between all IPC classes appearing under one citation ID (h), where $S_{h,i,j}$ is the number of times i and j appear in one citation as citing and cited 3-digit IPC class. For example, a patent in IPC class G02 that cites a patent co-classified in G02 and H01 will create a fractional count of 0.5 between G02 and G02 and of 0.5 between G02 and H01.

Since our goal is to construct a measure of citation links at the industry-country level, as a second step, we use the concordance scheme of Neuhäusler et al. (2019) to link IPC classes (k) with industries (l). This concordance scheme shows the probability weights of a specific industry in patenting in a technological field or an IPC class. We restrict this matching procedure to manufacturing industries (NACE 2) in the concordance table, i.e., economic sectors 10 to 30. For our analysis and for harmonization of the industry classification with the rest of the data sources, we match the NACE 2 classification with the ISIC v.4

classification of industries. Table 7 shows the list of industries after harmonization with all other data sources.

Third, we use the industry probability weight $\text{prob}_{k,l}$ to construct the *citation link* at the industry level. For that, we create a matrix of citation links between industries (m, n) using the citation weight of each individual citation with respect to IPC classes and the probability weight of the patent citation of both the citing and the cited industries. We aggregate the measure on citation link (i.e., as a weighted sum of citation links) by the citing industry. In equation 2, where we calculate the citation link, m refers to the citing industry and n refers to all cited industries in Germany, cited by industry m.

$$\text{CitationLink}_{m,n} = \sum_{k\in[i,j],l\in[m,n]} prob_{k,l}CW_{i,j} \tag{2}$$

In constructing the *citation link* measure on the industry level in equation 3, we follow an inter-industry approach where we aggregate the number of citations by each of the 14 industries citing itself but also citing any of the remaining 13 industries.

$$\text{CitationLink}_{m} = \sum_{n} \text{Citationlink}_{m,n} \tag{3}$$

Since we focus on knowledge spillovers from the customer to the seller, it seems relevant to consider vertical sources of knowledge with respective inter-industry spillovers that are associated with the cited industries (Belderbos & Mohnen, 2020). For instance, the electronics industry in a trading partner can cite technological fields in the German electronics industry, but we also allow for citations to technological fields associated with other industries in Germany. Finally, our data include the citing country, citation link at the industry level, and the priority year of the citing patent. The latter corresponds to the time frame of the analysis where other variables are available.

Independent variables

Our main independent variable is a *Spillover* measure based on the value of exported intermediate goods to Germany, extracted from the OECD Bilateral Trade Database by Industry and End-Use (BTDIxE). To do so, we follow Funk (2001) and construct the R&D spillover measure via exports, which is an extension based on the one proposed by Coe and Helpman (1995). We adapt this approach by analyzing data at the industry-country level rather than at the country level. Similar to Coe and Helpman (1995), Funk (2001) and others, who focus on foreign R&D as a source of productivity improvement at the domestic level, we treat German R&D as a source of knowledge from which trade partners can learn and build on by citing German patents. In contrast to Funk (2001), we focus on intermediate goods instead of total traded exports, as we expect a particularly sophisticated demand when goods are to be used as intermediates in manufacturing. Consequently, our spillover measure is constructed as follows:

$$\text{Spillover}_{m,c,t} = E_{m,c,t} \cdot R\&D^{\text{GER}}_{m,t} \tag{4}$$

The spillover measure is constructed for industry m in country c at time t. $E_{m,c,t}$ is the share of exported intermediate goods of country c in all intermediate goods exports at the industry level[1] and $R\&D^{\text{GER}}_{m,t}$ is the industry-level *German R&D expenditure*. Thereby, we capture the amount of knowledge accessible from the German R&D by exporting intermediates to German industries. For additional analysis and robustness checks, we change the construction of the *Spillover* measure as we have once based on non-intermediates exports and another time based on German patenting activity instead of R&D expenditure.

[1]It is calculated as the value of exported intermediate goods by an industry to Germany (*Total Intermediates Exports*) divided by the total sum of intermediate goods exported to Germany in that industry from all countries in our sample.

Table 1: Summary Statistics – Estimation Sample

Statistic	N	Mean	St. Dev.	Min	Max
Citation Link	4,844	9	22.8	0	281.7
Spillover	4,828	141	383	0	4,621
T. Intermediates Exports	4,828	947,306	1,789,471	0	21,238,491
T. Intermediates Share	4,828	60.4	33.4	0	100
Domestic R&D Expenditure	3,571	1,579	6,548	0	83,499
German R&D Expenditure	4,684	3,873	5,909	20	29,084
Inward FDI	4,480	694	1,801	−7,182.5	11,070.5

Table 2: Number of citations to German Patents by Intermediates Trading Partners

United States	13104	Netherlands	2004	Turkey	361
Japan	11875	Belgium	1850	Czech Republic	248
France	7139	Spain	1728	Norway	218
Italy	5917	Denmark	1372	Hungary	177
Switzerland	4918	Canada	1024	Ireland	141
Austria	3146	Finland	976	Slovenia	119
Korea	2835	Poland	498	Portugal	72
United Kingdom	2496	Australia	460	New Zealand	72
Sweden	2082	Israel	371	Greece	44

Note: unique citation counts for period 2004–2016 based on EPO patents and citations data

In addition, we control for *Domestic R&D expenditure* of the exporting country at the industry level measured in US millions of PPP dollars at current prices and for *Inward FDI* flows from Germany to the exporting country in millions of US dollars at the country level. We interpolate missing values for some of the industry-country observations in the R&D data and for some country observations in the FDI data. For R&D, we adopt a linear interpolation approach whereby missing values are predicted based on the available observations before and after the missing years. For missing FDI flows, we use the average value for all years, since many missing observations are at the beginning or end of the observation period and the data does not follow a particular trend. For absorptive capacity at the country level, we use data on the number of R&D employees per million inhabitants extracted from the World Bank Development Indicators. Table 1 shows the summary statistics for all variables used in the analysis. We also present the variables used for constructing the spillover measure: *Total Intermediates Exports* is the value of intermediate goods exported to Germany by a trade partner at the industry level and is measured in nominal terms, i.e., thousands of current US dollars. *Total Intermediates Share* refers to the share of intermediates with respect to the total exports of an industry in a trade partner. Both *German R&D expenditure* are measured in US millions of PPP dollars at current prices.

3.2 Descriptive Analysis

To supplement our econometric analysis, we present a brief descriptive analysis of the structure of German trade partners. The list of trade partners in our sample is provided in Table 2 with their total number of citations aggregated by the citing country for the whole period of analysis in 14 manufacturing industries. The US and Japan top the list of trade partners with the most citations to German patents, followed by OECD and EU economies.

The bubble chart in Figure 1 shows the distribution of trade partners with respect to their value of intermediate goods exports to Germany, as well as their citation links to German patents. The size of

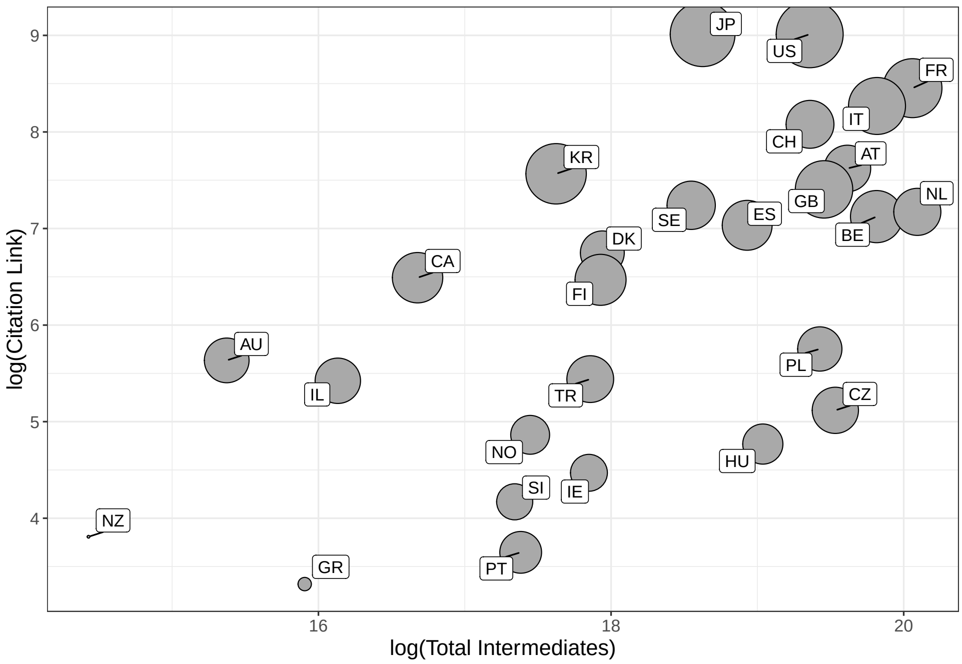


Figure 1: Citation link and volume of intermediates exports by citing trade partner
Source: own calculations based on OECD BTDIxE, REGPAT, Citations and R&D expenditure

each circle represents the aggregated R&D expenditure at the country level for the entire analysis period in all 14 manufacturing industries. In line with the total number of citations by a trade partner in table 2, the US and Japan have the highest level of citation links with German patents, while at the same time exporting a high volume of intermediate goods to Germany. As expected, EU economies that trade intensively with Germany are also involved in supplying Germany with intermediate goods that are used in subsequent production processes to produce the final good. These countries, in particular, France, the Netherlands, Italy, and Austria, also show a relatively high level of citations to German patents.

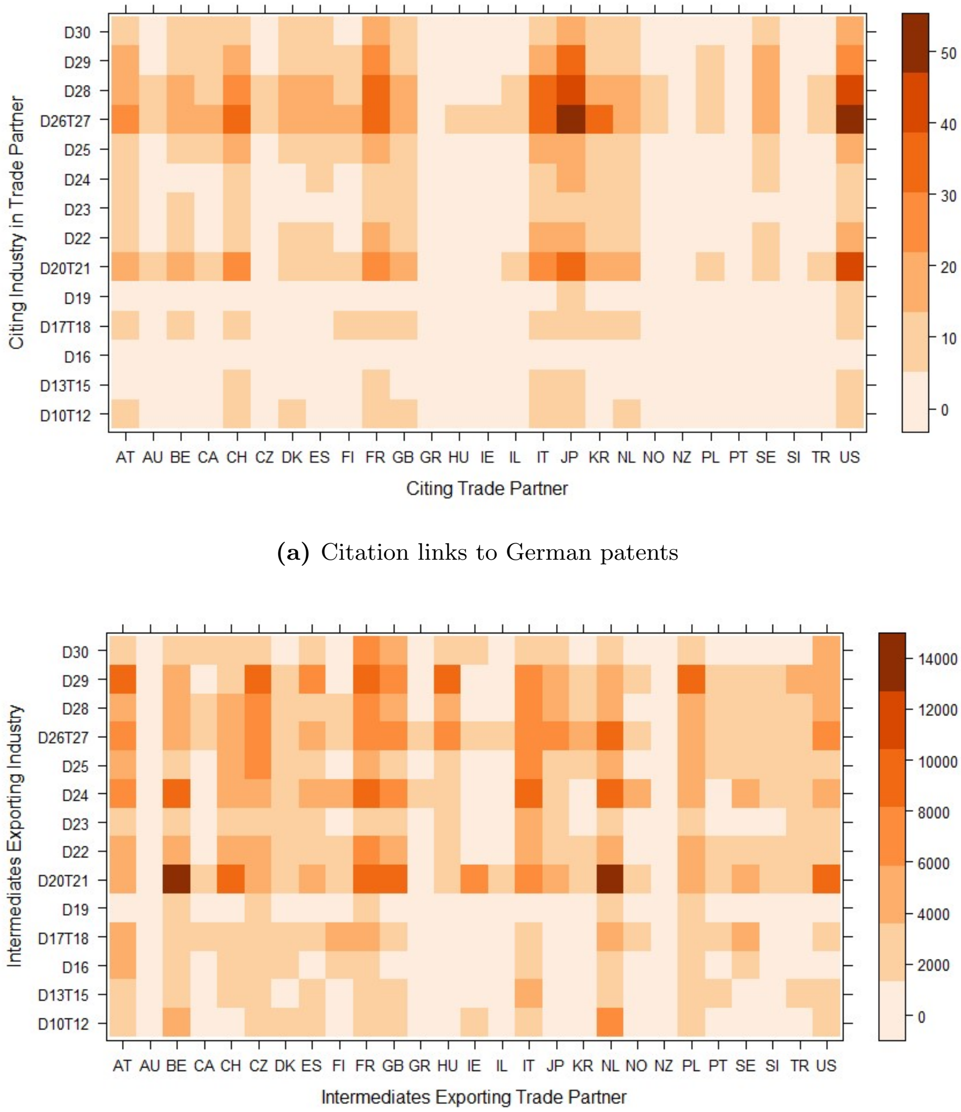
The heatmaps in figure 2 allow for a more detailed comparison of the citation links and value of exported intermediates to Germany at the industry level. In panel (a), the citing countries and industries are equivalent to the intermediates exporting countries and industries in panel (b). In both plots, industries D20T21 to D30 appear to have more citations to German patents and exported intermediates compared to the remaining industries and are those characterized by high technological intensity (Galindo-Rueda & Verger, 2016). In the next subsection, we present the empirical model where we test whether citation links to German patents can be explained by a spillover measure constructed on the basis of exported intermediate goods to one or more of the cited German industries.

3.3 Empirical Model

We aim to understand the extent to which learning in German value chains, as measured by citations to German patents, is explained by the export of intermediate goods to German industries. Given the long nature of our panel data, we use a fixed-effects model where we aim to capture the long-term variation in our independent variable on the *Citation Link* given our main variable of interest on the *Spillover* measure. Our main model is therefore specified as follows:

$$\begin{aligned} \ln(\text{CitationLink}_{m,c,t}) = \beta_1 \ln(\text{Spillover}_{m,c,t-2}) + \beta_2 \ln(\text{R\&D}^{\text{dom}}_{m,c,t-2}) + \\ \beta_3 \ln(\text{FDI}^{\text{in}}_{c,t-2}) + \mu_t + \mu_m + \mu_c + \varepsilon_{m,c,t} \end{aligned} \tag{5}$$

$\ln(\text{CitationLink}_{m,c,t})$ is our dependent variable constructed as presented in equation 3. The citing



(a) Citation links to German patents

(b) Exported intermediates to Germany

Figure 2: Citation links and exported intermediates by citing trade partners
Source: own calculations based on OECD BTDIxE, OECD REGPAT & Citations and Neuhäusler et al. (2019) for IPC-industry concordance.

industry m is the exporting industry of intermediate goods to German industries. Our main variable of interest is $\ln(\text{Spillover}_{m,c})$ as constructed in equation 4. We control for the domestic level of R&D expenditure at the industry-country level in each trade partner with $\ln(\text{R\&D}^{dom}_{m,c})$, as R&D spending is closely related to patent activity and innovation performance. We also control for FDI flows from Germany to each trade partner with $\ln(\text{FDI}^{in}_{c})$, as it is standard in the literature that FDI is considered a valid channel for knowledge spillovers and is important to boost innovation at the economy level (Ali et al., 2016). Also, the presence of multinational corporations in the form of FDI in trade partners can have an effect on the propensity to patent in general and to cite patents from their home countries (Piermartini & Rubínová, 2021). Our model takes into account time, industry and country fixed-effects accordingly, and $\varepsilon_{m,c,t}$ represents the error term. In order to address possible endogeneity concerns and, in particular, potential reverse causality, all right-hand-side variables are lagged by two years.

4 Results and Discussion

4.1 Main findings

Table 3 reports the results of the fixed-effects estimations. Model 1 corresponds to the fixed-effects model from estimating equation 5, while Model 2 additionally controls for dummy variables on interpolated missing values in both the R&D business expenditure and FDI data. So, for example, the dummy variable on interpolated R&D expenditure equals 1 in case the corresponding R&D value is interpolated and zero otherwise if the value is originally available in the data for an industry-country observation. Models 3 and 4 additionally control for industry-year fixed effects.

Table 3: Learning-by-exporting: intermediate goods exports to Germany as a spillover channel

Dependent Variable:	Citation Link			
Model:	(1)	(2)	(3)	(4)
Variables				
Spillover	0.1969***	0.1950***	0.2002***	0.1983***
	(0.0526)	(0.0530)	(0.0551)	(0.0554)
R&D Expenditure	0.0594**	0.0605**	0.0588**	0.0599**
	(0.0241)	(0.0236)	(0.0249)	(0.0244)
Outward FDI	-0.0113	-0.0121	-0.0113	-0.0121
	(0.0138)	(0.0134)	(0.0141)	(0.0138)
R&D_interp_dummy		-0.0442		-0.0450
		(0.0437)		(0.0461)
Inward FDI_interp_dummy		-0.0063		-0.0064
		(0.0289)		(0.0297)
Fixed-effects				
Citing Country	Yes	Yes	Yes	Yes
Citing Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry*Year	No	No	Yes	Yes
Fit statistics				
Observations	3,374	3,374	3,374	3,374
Within R^2	0.18442	0.18575	0.19864	0.19999
F-test	7.6954	7.1954	1.1940	1.1834

Notes: OLS fixed-effects panel regression (2004-2016). All variables in logs except dummy variables, and independent variables are lagged by two years. The spillover measure is the share of exported intermediate goods to Germany times German R&D expenditure per year and industry. Clustered (Citing Country) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

In general, we find a positive and statistically significant elasticity between citations to German patents, as represented by the constructed citation link, and the spillover measure based on exported intermediates weighted by German R&D. Specifically, we find that a one percent increase in the spillover measure is associated with a 0.20% increase in citations to German patents across all models. The magnitude of the estimated positive elasticity remains when controlling for the dummies on interpolated R&D and FDI values in model 2. As expected, R&D spending by domestic businesses is statistically significant and also positively elastic to citation links to German patents, although it shows a smaller magnitude compared to the spillover measure by about 0.14 percentage points. This shows that the export-relevant knowledge flows are more strongly associated with the citation of German patents than with domestic R&D expenditure.

We compare our estimates with those of similar studies to get a sense of the magnitude of trade related R&D spillovers and their correlation with patenting activity. In general, we find that our estimates are comparable to those of the relevant empirical work. Our estimate is larger than that of Funk (2001) of 0.11%. Funk (2001) is the first to use an export-weighted foreign R&D pool and study its relationship with domestic productivity at the country level. Our estimate is also larger than that of Piermartini and Rubínová's 2021 estimate (0.10% on average) who look at the elasticity between the foreign R&D pool weighted by GVC trade values and domestic patenting activity at the industry-country level. Our estimate is similar to the study by Sjöholm (1996), which finds a significant effect of trade flows on the referencing of Swedish patents by countries trading with Sweden (0.17%); however, the analysis does not distinguish between imports and exports and only considers the country level.

As can be taken from the heatmaps in panel (a) in Figure 2, some citing industries might have a higher propensity to innovate and patent than others. Industry D26T27 (Computers, electronic and electric equipment) shows the highest value for citation link with an average of about 39, while industries D28 (Machinery and equipment), D20T21 (Chemicals and pharmaceutical products), and D29 (Motor vehicles, trailers and semi-trailers) follow with average values of 28, 19, and 12 respectively. In addition, industries might experience some innovation shocks that could lead to an increase in its R&D spending and patenting activity (Belderbos et al., 2016; Piermartini & Rubínová, 2021). To address this concern, we run the analyses with additional controls for industry and year interaction to capture industry time-related shocks. Models 3 and 4 in Table 3 show that the findings of models 1 and 2 are not sensitive to such industry-year interactions.

4.2 Heterogeneous results by industry

We continue our analysis by examining the heterogeneity of the estimates across industries. To do this, we run our main fixed-effects models while interacting the spillover measure with a dummy for each industry. This allows us to test whether the learning premium observed earlier holds for all or some of the intermediates exporting industries in the trade partners. Figure 3 shows the estimated elasticities for the spillover measure by the exporting (citing) industry[2] compared with the main estimate from table 3. For most industry interactions, we find a positive sign; however, it is larger than the main estimate from table 3 and statistically significant only in some industries. The manufacture of machinery equipments (D28) shows the highest learning premium with an estimated elasticity of 0.32% increase in both models, followed by manufacture of computers and electronics (D26T27) with 0.28, chemicals and pharmaceuticals (D20T21) with 0.27, metal products (D25) with 0.21, rubber and plastics (D22) with 0.18, automotive and transport (D29 and D30) with an elasticity of 0.15 on average and food and beverage with 0.14. From this result, two observations are worth noting. First, the exporting industries with statistical significant learning premiums (except for food and beverage) are characterized by high levels of technological intensity as classified by the OECD and UNIDO (Galindo-Rueda & Verger, 2016). This finding is consistent with our hypothesis that learning is induced particularly when trading with

[2]The respective regression results are in the appendix, table 9.

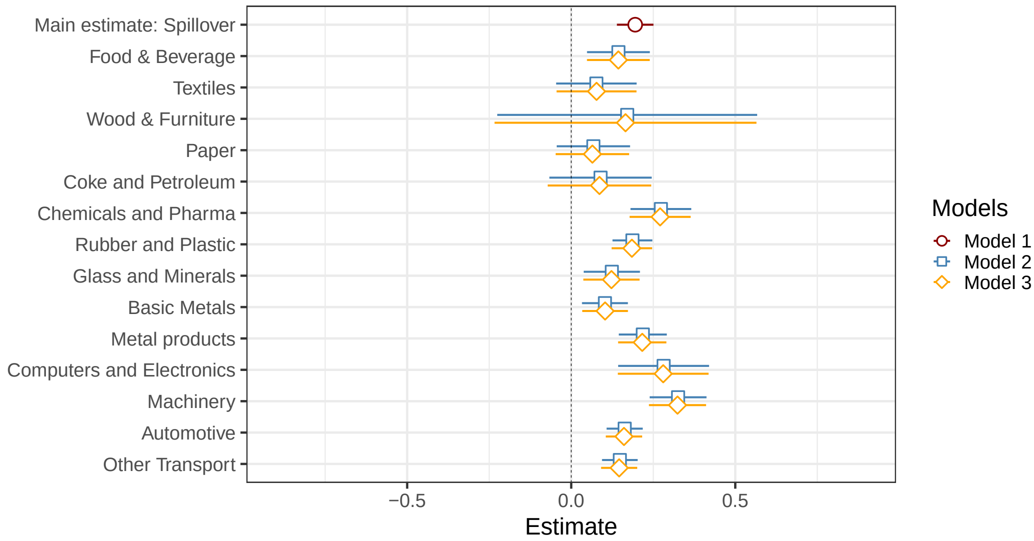


Figure 3: Regression results: heterogeneous learning by industry
Note: All variables are logged and dependent variables are in time lags of 2 years. Controls are added in all models. Model 1 is the baseline estimate from model 2 in table 3. Model 2 and 3 are from table 9

economies at the technological frontier. From this, we infer that the learning premium occurs in exporting industries that serve larger and more complex demands in Germany, which require innovation on the part of exporting industries to meet the needs of the German market. Second, the learning premium occurs in exporting industries that supply intermediate goods to industries in Germany that are known for their well-established technological advantages and strong patenting history. According to our data, some of these industries have the highest patenting activity in Germany (see figure 4).

4.3 Heterogeneous results by level of absorptive capacity

According to hypothesis 2, we expect that the level of absorptive capacity of a trade partner facilitates learning from German industries, given the share of intermediate goods exported to Germany. To test this hypothesis, we proxy the level of absorptive capacity with the number of R&D employees per million inhabitants in a trade partner. Similar to Piermartini and Rubínová (2021), we rank the trade partners according to their average number of R&D employees over the whole observation period. We then divide the list into three groups based on the interquartile range: the top 25%, the bottom 25%, and the middle group[3]. Countries in the top 25% include Finland, Denmark, Sweden, Korea, Norway, Japan, and Canada. The bottom 25% includes Turkey, Italy, Poland, Hungary, Greece, Spain, and the Czech Republic. The middle group, with a medium level of absorptive capacity, includes Australia, Austria, Switzerland, the United Kingdom, the United States, New Zealand, France, Ireland, Belgium, the Netherlands, Slovenia, and Portugal.

Table 4 shows the regression results for each of the subsamples. Our analysis shows that the level of absorptive capacity facilitates learning from German industries, given the level of intermediate goods exported to German industries. This result is statistically significant only for the subsamples with medium and highest levels of absorptive capacity. The magnitude of the estimated elasticity for the full sample (0.20) lies between the two estimated elasticities for the two subsamples with higher (0.16) and medium (0.25) absorptive capacity. This finding is in line with the literature which argues that a trade partner can only learn by exporting if the country has a sufficient level of absorptive capacity to patent, acquire and use external knowledge (Belderbos & Mohnen, 2020). Given the nature of the countries included in our

[3]Our sample in this analysis is reduced to 26 countries as we do not find data reported on the number of researchers involved in R&D in Israel.

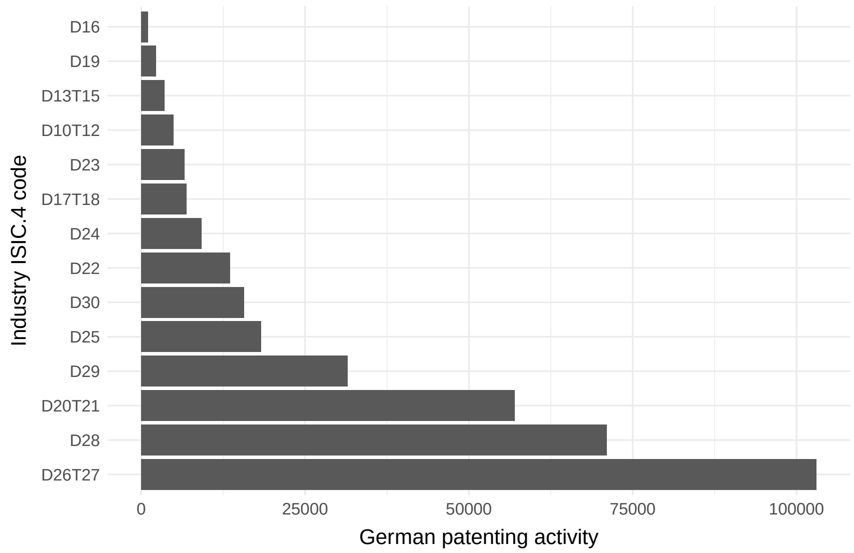


Figure 4: German patent activity by industry (2004-2016)
Source: own calculations based on OECD REGPAT. For aggregation at the industry level, we use the concordance developed by Neuhäusler et al. (2019).

sample, we also have countries that are known to be technologically advanced. Our result is in line with Ben-David and Loewy (1998), who find that countries with similar technological parameters and levels of economic growth tend to benefit from each other through trade flows. Foster-McGregor et al. (2017) also find that countries with higher levels of absorptive capacity, as measured by years of schooling and R&D expenditure, are those that benefit from foreign R&D spillovers. Firm-level evidence shows that firms with strong learning capabilities benefit most when supplying to technologically advanced firms, with this effect being more pronounced in foreign chains than in domestic ones (Belderbos & Grimpe, 2021). However, our results differ from many firm-level findings related to the learning-by-exporting hypothesis, which suggest that firms in less developed countries are able to improve their productivity by exporting to firms in technologically advanced countries (Blalock & Gertler, 2004; Martins & Yang, 2009). In our models 5 and 6, countries that are in the bottom 25% of our list in terms of their level of absorptive capacity do not learn as much by exporting as those in the top 25% or those in the middle. We argue that there are two reasons for the inconsistency between our results and firm-level evidence. First, we do not include countries with relatively low levels of economic development or low levels of absorptive capacity. Second, our empirical strategy differs from that of identifying learning by looking at changes in labor productivity (Foster-McGregor et al., 2017), total factor productivity (Coe & Helpman, 1995; Keller, 1998) or total production output (Blalock & Gertler, 2004). The technological input embodied in either goods or contacts facilitated by exports may provide better technological pathways for productivity improvement where these goods are used (Belderbos & Mohnen, 2020). However, as we focus here on learning through citing German patents, this implies that only certain countries may be able to benefit from technological fields in Germany and build on them by citing them in their own patents.

4.4 Other exports vs. intermediates as spillover channels

Following the mainstream of the literature on trade-related international R&D spillovers, we also examine the extent to which citation links to German patents can be explained by other exported goods compared to exported intermediate goods. In doing so, we adjust the weighting scheme in the construction of the spillover measure using data on total export trade, while excluding exported intermediate goods in equation 4. This means that we only take into account exported goods related to household consumption and finished capital goods. We again find support for the learning-by-exporting hypothesis. As shown in

Table 4: Learning-by-exporting by country level of absorptive capacity

Dependent Variable:	Citation Link					
	Country group: absorptive capacity					
	Top 25%		Middle 50%		Bottom 25%	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Spillover	0.1661*	0.1652*	0.2603***	0.2555***	0.1444	0.1470
	(0.0690)	(0.0689)	(0.0793)	(0.0783)	(0.0791)	(0.0782)
R&D Expenditure	0.0290	0.0319	0.0585	0.0592	-0.0059	-0.0072
	(0.0186)	(0.0159)	(0.0565)	(0.0562)	(0.0485)	(0.0474)
Inward FDI	-0.0816	-0.0942	0.0027	0.0011	-0.0299	-0.0299
	(0.0471)	(0.0560)	(0.0196)	(0.0211)	(0.0232)	(0.0220)
R&D_interp_dummy		-0.0737		-0.0925		0.0639
		(0.0774)		(0.0541)		(0.0800)
Inward FDI_interp_dummy		-0.0637*		0.0328		-0.1377
		(0.0313)		(0.0441)		(0.0887)
Fixed-effects						
Citing Country	Yes	Yes	Yes	Yes	Yes	Yes
Citing Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	923	923	1,265	1,265	1,008	1,008
Within R^2	0.16959	0.17715	0.30456	0.31176	0.08187	0.08959
F-test	3.0107	2.8374	4.3715	4.1258	0.99131	0.93478

Notes: OLS fixed-effects panel regression (2004-2016). All variables in logs except dummy variables, and independent variables are lagged by two years. The spillover measure is the share of exported intermediate goods to Germany times German R&D expenditure per year and industry. Clustered (Citing Country) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 5: Learning-by-exporting: non-intermediate goods exports as spillover channel

Dependent Variable:	Citation Link	
Model:	(1)	(2)
Variables		
Spillover	0.1276***	0.1262***
	(0.0365)	(0.0364)
R&D Expenditure	0.0762***	0.0773***
	(0.0250)	(0.0245)
Inward FDI	-0.0148	-0.0158
	(0.0143)	(0.0137)
R&D_interp_dummy		-0.0598
		(0.0431)
Inward FDI_interp_dummy		-0.0091
		(0.0282)
Fixed-effects		
Citing Country	Yes	Yes
Citing Industry	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	3,374	3,374
Within R^2	0.14772	0.15018
F-test	7.3287	6.8621

Notes: OLS fixed-effects panel regression (2004-2016). All variables in logs except dummy variables, and independent variables are lagged by two years. The spillover measure is the share of total exports excluding intermediate goods to Germany times German R&D expenditure per year and industry. Clustered (Citing Country) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 5, we find that the citation link to German industries is positively elastic to the spillover measure based on total trade excluding intermediates. Comparing spillover channels, exported intermediates explain more variation in our learning variable than the more general one based on capital goods and household consumption. As is well known, capital goods in particular contain a technological component in their production and have been shown to be a carrier of learning from German industries (Xu & Wang, 1999). The learning premium associated with other exports as a spillover channel shows an elasticity of about 0.13 (see Table 5) compared to 0.20 reported for exported intermediate goods (Table 3). We can conclude that there is a higher learning premium associated with exported intermediate goods for industrial use than with other exported goods in our sample. Intermediate goods vary more in quality depending on the demand of the industry in which these goods are used and in which the final good is produced (Funk, 2001). Therefore, it seems reasonable that a higher learning premium would be justified.

4.5 Robustness Checks

In the following, we perform a series of analyses with alternative data sources and specifications to check for the robustness of our findings. The results are summarized in table 6, where model 1 gives our main estimates as in table 3 for comparison.

Learning from other countries

Our main hypothesis is that the more trade partners export intermediate goods to German industries, the more they learn from these industries by citing German patents that combine technologies associated with these industries. One could argue that GVC integration, i.e., the ability to export intermediate goods to advanced economies, requires innovation capabilities in general and will therefore be reflected in higher patenting and respective citations regardless of the country of origin. In this sense, a foreign producer exporting to Germany would not only have to learn from German innovation, but would also identify relevant knowledge globally. To test whether it is direct learning through exporting or a more general innovation process with global knowledge integration, we compare our results with a model where the citation link is constructed globally.

To do this, we construct our citation link (main dependent variable) based on patents from all countries in our sample, excluding German patents and self-citations. The estimations in table 6 (model 2). In this table, we see the higher relevance of domestic R&D expenditure for the citation link to industries in all countries in our sample compared to the spillover measure. Comparing the magnitude of the coefficients for the spillover measure with that of our benchmark regression (table 6, model 1), we see a higher learning premium from German industries (0. 20%) compared to global knowledge sourcing (0.14%). We can summarize that, despite a clear indication of global knowledge sourcing induced by exporting to an advanced economy, there is a positive and higher learning premium coming from exported intermediates to German industries.

Potential bias in the EPO data

For our main analysis, we rely on the patent and citation data from the European Patent Office (EPO) to construct the citation link. By focusing on EPO applications, we might introduce a potential bias, in the sense that trade partners might register their patents at the EPO in order to maintain close economic relationships with Germany and also with other EU countries. In this case, we might be capturing an aspect of strategic patenting rather than learning from German patents. To address this concern, we reconstruct the citation link variable using data on patents and citations under the Patent Cooperation Treaty (PCT), where countries file patents to protect their inventions in a wide range of countries worldwide. We follow the same procedure as explained in the data section. Figure 5 compares the coverage of the PCT data with the EPO data in terms of the final number of patents of trade partners citing German patents for the period 2004 to 2016, based on counting the unique citation IDs of the citing-cited PCT patent applications. The PCT data have a much lower coverage of trade partners citing German patents than the EPO. However, it shows a similar ranking of trading partners citing German patents the most.

Using the PCT-based citation link to estimate the model as in equation 5, we find a positive elasticity between the spillover measure and citation links to German patents (table 6, model 3). While this result confirms our main findings, the magnitude of the spillover coefficient is substantially lower (0.12%). Nevertheless, despite the lower coverage in our sample of German patents cited by trade partners, a learning premium from the German industries explained by spillovers based on exported intermediates seems to persist even with alternative patent data.

Patent-based spillover measure

The accessible knowledge pool for exporters to Germany could be measured by the number of patents rather than by German R&D expenditure. Therefore, we construct the spillover measure (see equation 4) based on the share of exported intermediates weighted by annual German patenting activity instead of German R&D expenditure. Since German R&D expenditure and German patent filings are positively correlated (see correlation table 8), we expect a positive elasticity between this alternative spillover measure and citation links to German patents. We check whether the magnitude would change significantly if German patenting activity were considered as the main source of knowledge instead of German R&D. We construct the German annual patenting variable using data on German patents from the same source as above, namely the European Patent Office (EPO). Following the procedure described above, we link German patents to their respective technological fields (IPCs) and then link these IPCs to industries

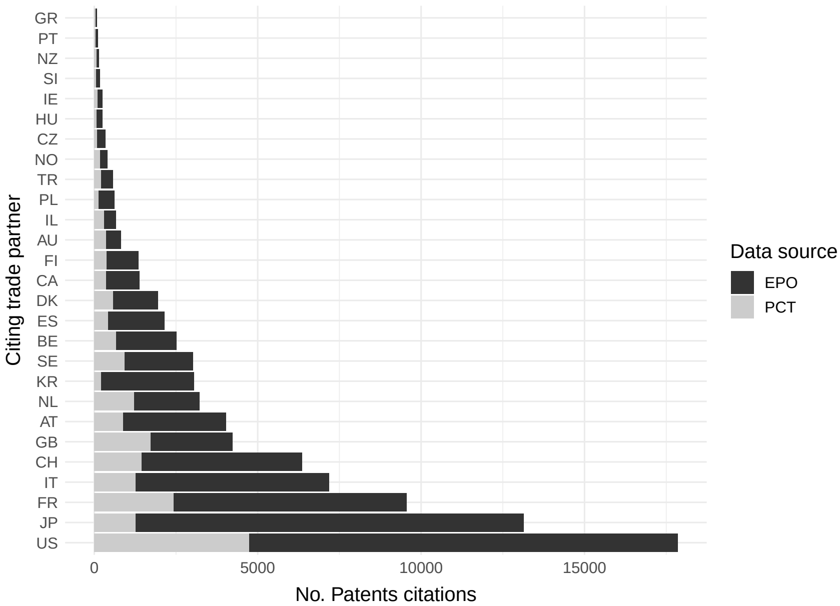


Figure 5: Number of citations to German patents by trade partners
Source: based on EPO and PCT patents data

using the probabilistic concordance scheme of (Neuhäusler et al., 2019). Our main finding regarding the positive elasticity between the citation link and the spillover measure remains robust to this alternative measure (see table 6, model 5). Similar to German R&D, German patenting activity can be seen as a source of knowledge that diffuses to industries in trade partners through the export of intermediate goods.

Table 6: Learning-by-exporting: comparing specifications and measures

Dependent Variables:	Citation Link	Citation Link to all	Citation Link PCT	Citation Link	
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Spillover Intermediates	0.1950***	0.1437***	0.1179***		
	(0.0530)	(0.0422)	(0.0378)		
Spillover non-intermediates				0.1262***	
				(0.0364)	
Spillover German Patents					0.1927***
					(0.0626)
R&D Expenditure	0.0605**	0.0995***	0.0460***	0.0773***	0.0650**
	(0.0236)	(0.0233)	(0.0139)	(0.0245)	(0.0245)
Inward FDI	-0.0121	-0.0210	-0.0079	-0.0158	-0.0126
	(0.0134)	(0.0131)	(0.0105)	(0.0137)	(0.0137)
R&D_interp_dummy	-0.0442	-0.0586	-0.0250	-0.0598	-0.0477
	(0.0437)	(0.0437)	(0.0200)	(0.0431)	(0.0433)
Inward FDI_interp_dummy	-0.0063	-0.0265	0.0047	-0.0091	-0.0082
	(0.0289)	(0.0363)	(0.0244)	(0.0282)	(0.0288)
Fixed-effects					
Citing Country	Yes	Yes	Yes	Yes	Yes
Citing Industry	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	3,374	3,374	3,374	3,374	3,374
Within R^2	0.18575	0.16634	0.11434	0.15018	0.16992
F-test	7.1954	12.030	4.1786	6.8621	7.0435

Notes: OLS fixed-effects panel regressions (2004-2016). All variables in logs except dummy variables, and independent variables are lagged by two years. Model 1: main FE estimate. Model 2: dependent variable is citation link to all countries in sample excluding Germany and self-citations. Model 3: dependent variable is citation link constructed based on PCT patents and citations data. Model 4: independent variable is spillover constructed as share of exports (excluding intermediates) weighted German R&D. Model 5: independent variable is spillover constructed as share of intermediates weighted German patenting activity. Clustered (Citing Country) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

5 Conclusion

The literature on productivity and endogenous growth has already established that a country's own productivity is enhanced by its domestic R&D activities as well as by knowledge spillovers from foreign R&D. There are various channels through which knowledge spillovers can potentially be transmitted, such as foreign direct investment (FDI), the mobility of workers and researchers, and trade. Based on the empirical literature, there is substantial and convincing evidence to support the notion that trade flows serve as a fundamental mechanism for knowledge spillovers. However, the empirical literature has focused intensively on import flows compared to exports and mainly on the overall level of trade rather than on intermediate goods. As import flows can diffuse knowledge that is beneficial for domestic productivity in the long run, exports can promote learning-by-doing, as the intensity of the contact embodied in export flows can facilitate learning from technologies in the importing countries. This paper is motivated by the learning-by-exporting hypothesis and examines whether knowledge spillovers can flow from customers positioned at the technological frontier, such as Germany, to the exporter, represented by a sample of 27 trade partners. We follow Coe and Helpman (1995) and Funk (2001) in constructing the spillover measure and examine whether there is a learning premium from German R&D channeled through exported intermediate goods by trade partners. As argued by Funk (2001), exports are more likely to facilitate pure knowledge spillovers, which is why we restrict our learning measure to patent citations as a direct proxy for learning from German industries. While the empirical literature has focused on country-level analyses of trade-relevant spillovers, we contribute to the literature by integrating the industry dimension into our analysis by linking patent citations to industries based on a probabilistic scheme of technological fields and economic sectors. Using data at the industry-country level, including patent citations, R&D expenditure, trade in intermediate goods and FDI flows, we find a positive elasticity between the export of intermediate goods and learning.

We restrict our data and analysis to manufacturing industries, given their high level of trade along GVCs, especially in intermediate goods and goods. Based on our industry analysis, we find that industries in the exporting countries show a heterogeneous pattern of learning from trade with German industries. It seems that the trade partners benefit especially in those industries where Germany has a traditional technological strength such as computers and electronics, metals, machinery, automobiles, chemicals and pharmaceuticals. We also show that the level of absorptive capacity of a trade partner plays an important role in absorbing spillovers from Germany, as trade partners in the top and middle of the absorptive capacity ranking seem to learn the most from German industries. These patterns remain consistent when using an alternative spillover measure based on German patents and across different scenarios, as we find that the export-relevant learning premium from German industries is higher.

In this paper, we provide some insights into spillovers from the customer to the seller side of the value chain. Despite several robustness checks, we still have to acknowledge some limitations. We restrict our learning variable, which is our outcome variable, to patent citations. Although patent citations are an imperfect measure of learning as not all innovative activities are patented, it is a direct indicator of knowledge flows and combines the technological relevance of the citing industry as well as its absorptive capacity (Belderbos & Mohnen, 2020). Additionally, patent citations have been previously used to study the role of trade in facilitating international knowledge flows (Sjöholm, 1996). Therefore, we do not capture other types of knowledge flows or improvement recommendations that could be transmitted from the German side to the exporting industries in other countries. Moreover, the propensity to patent is higher in some industries than in others (Belderbos & Mohnen, 2020). As spillover channel, we use exported intermediate goods in the upstream value chains of German industries. Even though trading in intermediates does not capture GVC participation completely, it involves a substantial share of it. It is estimated that trading in intermediate goods account for 85% of global trade and is usually used as a strong proxy for GVC participation (UNCTAD, 2021). It has also been shown that technology transfer through trading in intermediate goods is significant compared to other types of goods (Keller, 2002). In addition, we have a limited range of trade partners in our sample, where some important German trade partners, such as China or South American countries, are not included due to a lack of data, in particular, data on FDI flows to these countries. Therefore, we cannot generalize our findings to other countries, as most of the trade partners included in the sample are OECD or EU economies. This limits our understanding of whether less developed or emerging economies could also learn from German industries via the export of intermediate goods to these industries. This should be done with a richer data set and a larger sample of countries.

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Appendix

Table 7: List of Industries - ISIC v.4

Industry Name	Industry Code
Food products, beverages and tobacco	D10T12
Textiles, wearing apparel, leather and related products	D13T15
Wood and products of wood and cork	D16
Paper products and printing	D17T18
Chemicals and pharmaceutical products	D20T21
Coke and refined petroleum products	D19
Rubber and plastic products	D22
Other non-metallic mineral products	D23
Basic metals	D24
Fabricated metal products	D25
Computers, electronic and electric equipment	D26T27
Machinery and equipment	D28
Motor vehicles, trailers and semi-trailers	D29
Other transport equipment	D30

Table 8: Correlation Table of variables used in analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1 CitationLink		0.81 ***	0.92 ***	0.35 ***	0.77 ***	0.28 ***	0.18 ***	0.35 ***	0.36 ***	0.58 ***	0.47 ***
2 CitationLink PCT			0.79 ***	0.44 ***	0.77 ***	0.29 ***	0.17 ***	0.39 ***	0.40 ***	0.63 ***	0.49 ***
3 CitationLink all				0.30 ***	0.82 ***	0.26 ***	0.13 ***	0.29 ***	0.31 ***	0.52 ***	0.46 ***
4 T.Interm					0.27 ***	0.30 ***	0.08 ***	0.72 ***	0.59 ***	0.77 ***	0.29 ***
5 Dom. R&D						0.23 ***	0.12 ***	0.26 ***	0.28 ***	0.36 ***	0.28 ***
6 GER R&D							0.00	0.57 ***	0.58 ***	0.35 ***	0.61 ***
7 FDI								0.05 ***	0.06 ***	0.10 ***	0.00
8 Spillover (1)									0.75 ***	0.70 ***	0.35 ***
9 Spillover (2)										0.61 ***	0.35 ***
10 Spillover (3)											0.58 ***
11 GER Patent											

Spillover(1): share of exported intermediates weighted German R&D
Spillover(2): share of total exported goods (excl. intermediates) weighted German R&D
Spillover(3): share of intermediates weighted German patenting activity
Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

Table 9: Learning-by-exporting by industry

Dependent Variable:	Citation Link	
Model:	(1)	(2)
Variables		
Spillover × D10T12: Food & Beverage	0.1439**	0.1437**
	(0.0688)	(0.0690)
Spillover × D13T15: Textiles	0.0767	0.0771
	(0.0849)	(0.0850)
Spillover × D16: Wood & Furniture	0.1707	0.1654
	(0.2515)	(0.2541)
Spillover × D17T18: Paper	0.0675	0.0645
	(0.0763)	(0.0766)
Spillover × D19: Coke and Petroleum	0.0894	0.0861
	(0.1003)	(0.1020)
Spillover × D20T21: Chemicals and Pharma	0.2733***	0.2710***
	(0.0632)	(0.0640)
Spillover × D22: Rubber and Plastic	0.1865***	0.1849***
	(0.0471)	(0.0481)
Spillover × D23: Glass and Minerals	0.1237**	0.1226**
	(0.0442)	(0.0444)
Spillover × D24: Basic Metals	0.1028*	0.1032*
	(0.0517)	(0.0513)
Spillover × D25: Metal products	0.2182***	0.2165***
	(0.0505)	(0.0511)
Spillover × D26T27: Computers and Electronics	0.2816***	0.2803***
	(0.0933)	(0.0935)
Spillover × D28: Machinery	0.3257***	0.3240***
	(0.0602)	(0.0608)
Spillover × D29: Automotive	0.1629***	0.1608***
	(0.0419)	(0.0424)
Spillover × D30: Other Transport	0.1482***	0.1461***
	(0.0393)	(0.0399)
R&D Expenditure	0.0610**	0.0619**
	(0.0226)	(0.0222)
Inward FDI	-0.0109	-0.0116
	(0.0140)	(0.0136)
R&D_interp_dummy		-0.0411
		(0.0432)
Inward FDI_interp_dummy		-0.0103
		(0.0285)
Fixed-effects		
Citing Country	Yes	Yes
Citing Industry	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	3,374	3,374
Within R^2	0.24649	0.24767
F-test	5.7346	5.4772

Notes: OLS fixed-effects panel regression (2004-2016). All variables in logs except dummy variables, and independent variables are lagged by two years. The spillover measure is the share of exported intermediate goods to Germany times German R&D expenditure per year and industry. Clustered (Citing Country) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1

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