Innovation and Technological Content of Imports

Final Report

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Contents

Executive summary

- The importance of international trade for innovation and then ultimately economic growth has long been recognized. But, one of the main motivations for that link, the diffusion of ideas via the technological content of trade, has been elusive because of the challenge in moving between product-level data and technology-level information. In particular, failure to recognize the diffusion of similar technologies via other products potentially underestimates the importance of the exposure to new ideas in the generation of new innovations.

- We contribute, by using the concordance of Lybbert and Zolas (2014), to analyze patenting in nearly 200 countries over a 35 year period across more than 600 technological classes. We find that exposure to overseas innovation via imports is the main driver of positive international innovation spillovers.

- After controlling for diffusion, we find that import competition lowers innovation while imported inputs have no significant effect. This latter finding suggests that the existing literature may be misallocating the benefits of diffusion to these alternative trade-related effects.

- Across a range of robustness checks, including controlling for other determinants of patenting (such as international research collaborations), subsamples of developed and developing countries, different time periods, and focusing only on high-quality patents, we consistently find that the trade-driven international innovation spillovers are mainly driven by the exposure to the technological content of imports.

- Our findings also show a positive effect of international connections between inventors suggesting that international social network plays a key role for the diffusion of knowledge from one country to another. As many of the international research collaborations happen within multinational enterprises (MNEs), this evidence should also be linked with the role of multinationals in the international diffusion of knowledge.

- Recognizing not just the net innovation increasing effects of imports but its underlying conflicting effects has important policy implications. In particular, our results suggest that not all imports are alike in their ability to stimulate local innovations because not all trade contains all technologies. Importing from technology leaders should have larger spillovers on local innovative abilities. This then points more towards implementing lower scale trade agreements (e.g. regional trade agreements) than broad-based border opening (such as under the World Trade Organization).

- Furthermore, the evidence that past international research collaborations promote current innovations also fuels the debate about the effects of protectionnist and isolationnist policies on a country's innovative abilities. In particular, this argues against the current push against the international flow of skilled labour as embodied in policies such as Brexit.

1 Introduction

Even before the seminal rigorous discussions of Duesenberry (1956) and Solow (1956), there has been an obvious link between economic growth and technological progress. Understanding the mechanisms driving this link is crucial for tackling the many challenges facing the world including climate change and income distribution. Although there is a myriad of analysis examining innovation and its determinants, one that has received a particular interest is how innovation in one location spills over to affect innovations in another. This operates both on a sub-national level and internationally. Early contributions in the area such as Jaffe (1986) find that these innovation spillovers are negatively correlated with distance, a result that has been found repeatedly. This then begs the question of why that should be so, with the common thread across the explanations boiling down to the notion that certain activities act as conduits for technology and that those connections become more tenuous with distance. In an international context, trade is the conduit that has received the lion's share of attention both because of its ubiquity and the fact that it tends to fall with the distance between countries.

Theoretically, this led to several papers connecting trade, technological progress, and growth (e.g. Romer (1990) and Grossman and Helpman (1991)).[1] A key aspect of these models is that trade embodies technology which sparks the imagination of researchers in the importing country. This diffusion effect then leads to more innovation because it lowers the cost of local innovation as domestic researchers are able to build upon the ideas contained in the products entering their country.[2] Testing this diffusion effect, however, has proven difficult for two reasons. First, there is the challenge of describing which technologies are embodied in a particular

[1] See Kiriyama (2012) and Keller (2004) for surveys on the literature connecting trade, technological progress, and growth.

[2] Note that when we say "diffusion", we refer not to the implementation of an existing patent-embodied technology which need not imply the generation of new patents.

product. Since trade data is available by product, not technology, this is a significant barrier. Second, if one then chooses to examine innovation at the product or industry level, this ignores the diffusion effect from other products. For example, importing a laptop can generate ideas that leads to innovation in mobile phones. Thus, working with a product or industry potentially underestimates the diffusion effect. In this project, we address this issue by employing the product-technology correspondence of Lybbert and Zolas (2014) to convert trade in products to trade in technologies. This allows us to estimate the impact of diffusion on patenting activity across 187 countries and 652 technology classes over 1978-2013. We find a robust effect of diffusion that, in our preferred specification, suggests an elasticity in which a 10% rise in exposure to diffusion increases local patenting by 0.51%.

Diffusion is not, however, the only avenue by which imports can affect local innovation. A second route by which this can occur is the increase in competition from rising imports. Here, the theory suggests two conflicting effects (see Raith (2002) or Aghion, et al. (2005) for discussion). First, rising competition lowers a firm's residual market, eroding the value from innovation. Alternatively, simply in order to survive, a firm may be forced to innovate so as to remain competitive. Although the theoretical expectation is ambiguous, the evidence generally points to innovation increasing effects from import competition with recent examples including Bloom, Draca, and van Reenen (2016) and Coelli, Moxnes, Ulltveit-Moe (2016). Second, importing intermediate inputs can also affect the value from innovation because it lowers the costs of production by providing new intermediates (Goldberg, et al., 2010) or less expensive ones (Liu and Qiu, 2016). As this increases sales, it serves to increase the desire to innovate, a prediction the existing literature tends to support. A challenge for the existing literature is that diffusion, import competition, and imported inputs are all positively correlated with one another. While studies such as Bloom, Draca, and van Reenen (2016) account for both import competition and inputs, as noted above, they have yet to be able to control for diffusion. When we omit diffusion, we find positive effects from import competition and imported inputs, results in line with the existing literature. However, when including our diffusion variable, import competition becomes significantly negative and imported inputs no longer have an effect on innovation. This suggests that the lessons learned from the existing literature may need to be considered more carefully if their results are sensitive to the omission of diffusion as well.

Across a range of robustness checks, including controlling for other determinants of patenting (such as international research collaborations), subsamples of developed and developing countries, different time periods, and focusing only on high-quality patents, we consistently find that the trade-driven international innovation spillovers are mainly driven by diffusion, that is, the exposure to the technological content of imports. Understanding this is important for several reasons. First, it suggests that to encourage domestic innovation, it may be necessary not only to open one's borders but to seek out particular trade agreements with leaders in the technologies one hopes to work on. Second, in line with the concerns of Keller (2002), it points to the possibility that trade agreements among the world's technological leaders may lead to income divergence. Finally, the current political climate is one in which the trend is towards isolationism with technological leaders such as the US and the UK looking to close their borders to imports and immigration. Based on our estimates, this would have a cooling effect both for themselves and for their trading partners.

2 Literature Review

In the literature discussing the connection between importing and innovation, three different links have been put forward, each operating off of a different aspect of innovator behaviour: import competition (which affects the demand for a firm's output), the importing of intermediate inputs (which impacts production costs), and diffusion (which alters innovation costs).[3] To frame the differences across these and better structure the discussion of the existing work, consider the following simple model of a profit maximizing innovator. The firm's profit function depends on its own output q, its own level of innovation i, and imports. Imports can be those of its competitors m^C, its own imports of intermediate inputs m^I, or exposure to the ideas of others m^D. Profits can be written as:

$$\pi\left(q,i,m^I\right) = r\left(q,i,m^C\right) - c\left(q,i,m^I\right) - \phi\left(i,m^D\right) \tag{1}$$

which is revenues less production and innovation costs. For the sake of simplicity, assume that revenues are strictly concave in output and innovation and that production (innovation) costs are strictly convex in output (innovation). This framework allows for two benefits from innovation: increasing revenues (product innovation) and/or lower production costs (process innovation).

Turning to imports, each of the channels affects a different aspect of the optimal innovation level which is where marginal benefit equals marginal cost:

$$r_2\left(q,i,m^C\right) = c_2\left(q,i,m^I\right) + \phi_1\left(i,m^D\right) \tag{2}$$

As imported intermediates rise, all else equal, this lowers production costs ($c_{23} < 0$). This can happen via simply providing cheaper inputs (Liu and Qiu, 2016) or introducing new intermediate inputs (Goldberg, et al., 2010). This gives the firm an incentive to increase output which can then lead to an incentive to further innovate.[4] Likewise, as diffusion rises, this lowers innovation costs (see for example the theory of Romer (1990) and Grossman and Helpman (1991) or the empirical contributions

[3] Note that imports are not the only measure of globalisation since this leaves out the role of exports and foreign direct investment, both inbound and outbound. Here, however, we focus on imports for brevity's sake.

[4] Note that this requires that c_{23} is not too negative so that a reduction in costs via imported intermediates does not lower the net incentive for process innovation. If innovation is purely for product purposes, this is not a concern.

of Coe and Helpman (1995) and Acharaya and Keller (2008)). This then leads to more output and innovation.[5]

As discussed by Aghion, et al. (2005), the effect from import competition is more complex and depends on the nature of demand changes as import competition increases. One possibility is that an increase in import competition marginally lowers sales and therefore creates a marginal decline in the return to innovation. In this case, a rise in import competition would lead to a reduction in innovation because the number of consumers across which the firm can spread innovation costs (or extract addition income from) is smaller. A separate possibility is where competition is more fierce so that a rise in import competition causes a discrete change in the return to innovation. For example, suppose that demand is Bertrand-like so that consumers purchase only the newest generation of a product. In this case, unless the firm undertakes innovation, sales fall to zero. Thus, rather than creating a marginal reduction in the return to innovation, import competition creates a discrete rise in the return to innovation (i.e. it either innovates to survive or goes out of business).[6] This means that innovation can rise in the face of import competition. As such, import competition can have an ambiguous effect on innovative activities.

With this framework in hand, we now turn to the existing literature. Early contributions operate at an aggregated level and explain changes at the country level by the import-weighted innovation elsewhere. For example, Coe and Helpman (1995) find that import-weighted foreign R&D capital stocks increase domestic total factor productivity (TFP), particularly when a country's imports are high.[7] van Pottelsberghe de la Potterie and Lichtenberg (2001) confirm this result when adding in inbound and outbound foreign direct investment whereas Coe, Helpman, and Hoffmaister (2009) do so with an alternative dataset and additional institutional controls. As discussed by Madsen (2007), who analyzes over a century of data for the OECD,

[5]Note that this holds for both product and process innovation.

[6]See Raith (2003).

[7]Fracasso and Marzetti (2015) find that the relationship is highly non-linear in imports.

the trade linkages can be significant, as much as 93% of the change in TFP in his analysis. These contributions, however, have three limitations. First, by operating at the aggregate level, they are combining imports across industries and thus weight by trade which may be irrelevant, adding noise into the estimation. This can be deal with by, for example, using country-industry data as in Keller (2002). Although he does not weight foreign R&D by trade, he does so by distance and common language measures, finding evidence of positive R&D spillovers, however, these are declining in distance and are positively related to common language (a pattern consistent with observed trade volumes). Second, they do not provide direct evidence of imports affecting innovation *per se* since they look at TFP rather than local innovation measures. However, if imports drive local innovation which drives TFP growth, this is again consistent with the overall framework. Third, they do not distinguish across the three channels by which imports can impact innovation and instead estimate a net effect. This, however, can cloud potentially offsetting effects such as a positive diffusion impact at the same time as a negative import competition one.

The more recent literature has responded to these three issues by using more micro-level data, employing more direct measures of innovation, and attempting to isolate the various channels by which imports affect innovation. One way to do so is to focus narrowly, such as in case studies of Bugamelli, et al. (2008), Bartel, et al. (2007), or Freeman and Kleiner (2005) who, for a narrowly defined country and industry, consider the impact of import competition (often concluding that competition induces innovation).[8] Closer to our analysis, however, are cross-country studies. For example, Bloom, Draca, and van Reenen (2016) use firm-level data across Europe to examine the impact of an increase in imports from China. Matching firm-level information to patent ownership, investment in information technology, and TFP, they find that exposure to Chinese imports in a firm's industry rises, so does its innova-

[8]Beyond the amount of innovation, some studies suggest that import competition leads to more complex patents (see Liu and Rosell, 2013).

tive activity.[9] Arguing that, due to their generally low level of innovation, Chinese firms should not provide much in the way of new technologies, they attribute this to a positive effect from import competition. In addition, using input-output tables to link Chinese imports to intermediates, they find that an increase in imported intermediates from China leads to more information technology investment and higher TFP, although it has no significant impact on patenting. Similarly, Coelli, Moxnes, Ulltveit-Moe (2016) consider the impact of tariff liberalization within a firm's three-digit industry on its patent applications. When tariffs decline, this again leads to greater patenting which they interpret as higher import competition.[10]

While these papers focus on the import competition effect, others aim to isolate the imported inputs impact. Harkening to the early work using TFP, Halepern, et al. (2011) or Kasahara and Rodrigue (2008) find that increases in imported intermediates leads to higher productivity. Using the introduction of a new product as a measure of product innovation, Goldberg, et al. (2010) find that reduction in tariffs on imported intermediates leads Indian firms to introduce new products. A comparable result is found across European countries by Colantone and Crino (2014). In contrast, Liu and Qiu (2016) find that a reduction in import tariffs actually led to a reduction in patenting by Chinese firms. They attribute this to an ability to secure high-quality inputs from abroad which crowds out the need for local innovation.[11]

Thus, the existing literature finds an overall positive effect of imports on innovation using various measures (direct and indirect) of innovation, data at differing levels

[9]Further, they find that, in line with Melitz (2003), there is a shift in activity to more productive firms, firms which also tend to innovate more.

[10]In line with the market size impact of import competition, Coelli, Moxnes, Ulltveit-Moe (2016) test for the impact of exporting on innovation, again finding a positive effect. This suggests that access to a larger market via exporting increases innovation, something supported by the single country studies of Bustos (2011) and Teshima (2008). Note that that stands in contrast to the positive import competition effect they also find. Guadalupe, Kuzmina, and Thomas (2012) who analyze the effect of foreign ownership on innovation find that a large part of the boost in innovation due to foreign acquisition is via access to export markets via the parent firm.

[11]Recall that in the above model, this is theoretically possible.

of aggregation, and attempts at isolating a specific channel, either import competition or imported inputs. One feature missing from these studies, however, is the diffusion channel. A key reason for this is that this literature operates in product space. Even when using firm-level data, the trade variable is that related to a firm's industry. This, however, misses a key aspect of technological diffusion: that it can spill across products. For example, imports of a laptop can generate ideas for use in a smartphone and vice versa. However, the approach of the existing literature would consider only laptop imports for laptop innovation, thereby missing out on the total exposure to relevant innovation embodied in products. This is the key contribution of our analysis.

In addition, as with Bloom, Draca, and van Reenen (2016), we control for multiple channels at once, adding diffusion to the import competition and input effects. In our results, this is key because, when not controlling for diffusion, we find a significantly positive effect for import competition and imported inputs. This is consistent with the results above. When doing so, however, we find that diffusion drives those positive effects with import competition becoming significantly negative. This suggests that some of the innovation inducing results attributed to competition may be driven by omitted variable biases. While Bloom, Draca, and van Reenen (2016) aim to limit that by focusing on Chinese imports which they argue may have little innovative content, this still presupposes that developed countries cannot be inspired by ideas originating in their less-developed trading partners. As with the lack of cross-product diffusion, this may miss a key part of the dissemination of knowledge and the inspiration effects this has.

3 Data and Empirical Approach

In order to examine the effect of imports on patenting, we build on the approach of Bloom, Draca, and van Reenen (2016), Coelli, Moxnes, Ulltveit-Moe (2016), and others and use the count of new patents as our dependent variable. Specifically, our baseline estimation equation for the count of patents in country i in the four-digit technology class c in year t is:

$$Patents_{i,c,t} = exp(\beta_1 lnK_{i,c,t-1} + \beta_2 lnComp_{i,c,t-1} + \beta_3 lnDiffuse_{i,c,t-1} + \beta_4 lnInput_{i,c,t} + \beta_5 lnSocial_{i,c,t-1} + \beta_6 lnDist_{i,c,t-1} + \gamma_{i,c} + \gamma_{i,t}) + \varepsilon_{i,c,t}. \quad (3)$$

In this, $K_{i,c,t-1}$ is the existing stock of patents, $Comp_{i,c,t-1}$ through $Dist_{i,c,t-1}$, are variables relating to the other countries (described below), the γs are fixed effects, and $\varepsilon_{i,c,t}$ is the error term.

As discussed above, our dependent variable differs from the existing literature in that it operates at the technology class level rather than the industry level so as to better capture cross-product diffusion effects. For our patent data, we draw from the US patent office (USPTO) where we have patent data from 1978 to 2013.[12] Note that we use applications, not only granted patents, where for the sake of brevity, we refer to applications (whether ever granted or not) as patents. We use applications because not all applications are granted, nevertheless, the innovations contained in unsuccessful applications can still create a diffusion effect.[13]

USPTO data seem to fit for studies in an international context and have been com-

[12]We end the sample in 2013 because, after that date, we observed a significant drop off in the number of patent applications. As is well known, end of sample truncation is an issue in patent data.

[13]Carly, Hegde, and Marco (2015) find that only about two-thirds of US patents are granted.

monly used in the related literature (e.g. Branstetter, 2006; Luintel and Khan, 2017). Indeed, the US being the largest economic market benefiting from high intellectual property rights, the USPTO receives a very important number of applications including inventors from outside of the US. In our original dataset 50,9% of inventors are non-US residents.

However, we are also aware that there is a home bias if one uses a single territorial patent database. US residents could be overrepresented as compared to other countries. The distribution of non-US inventors might also be biased towards countries closer, or with closer ties, to the US. In that case, cross-country differences in applications to USPTO might generate a biased measure of the absolute amount of knowledge generated in a country[14]. We try to overcome these potential issues (i) through our econometric strategy and (ii) by relying on an alternative source of patent data as robustness. Indeed, the inclusion of country and CPC specific fixed effects in our empirical specification should capture in our estimations any systematic difference in applications to USPTO at the country-CPC level. But, to ensure that the construction of our variable of technological content of imports - that uses bilateral partners' stock of patents - is not biased, we also extract and utilize as robustness an alternative source of data that should not suffer from such any such bias as described below. We rely on data on patents applied in the patent offices of Europe, the US, Japan, Korea, and Australia which contains information from 2000 to 2013. These data come from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT).[15] In particular, this database gives us information on patent families so that we can observe which patents are submitted to multiple offices. Akin to Coelli, Moxnes, Ulltveit-Moe (2016), we also use the subsample of patents filed in all five offices (pentadic patents) as a way of restricting

[14]The same bias might of course occur when considering patents from any other single patent office

[15]Note that the raw data from PATSTAT is available before 2000. However, due to the important extra treatment and processing work load required for the collection of the pentadic applications on a global scale, we have truncated the time-span of this dataset to start in 2000 instead of 1978.

our estimates to "high-quality" patents.[16]

From each patent, we extract several items of information. First, we obtain the priority date which we use as the year of a patent's creation. Since we use applications, not just granted patents, this is necessary. In addition, using the priority date has the added benefit of bringing the date of the innovation closer to the point of its actual genesis. Second, we obtain the list of inventors which includes their country of residence at the time of invention. We use this to fractionally allocate a patent to a country, where when inventors from n different countries are listed on the patent, $\frac{1}{n}$ of the patent is allocated to each of the n countries. For our purposes, there are two advantages to using inventor locations rather than those of the assignee (the owner). First, this arguably locates the innovation more closely to where the ideas are generated. This is important when discussing diffusion. The second advantage is that, unlike the location of assignees, inventor location may be less influenced by, for example, tax policies across borders.[17] Finally, we obtain the list of four digit technology classes listed on the patent.[18] Comparable to the inventor allocation, when r technology classes are listed, we allocate $\frac{1}{r}$ of the patent to each of the listed classes. Thus, our dependent variable is a weighted sum of patents in i, c, t after accounting for the shares of inventors and classes. In our largest sample, this leaves us with an unbalanced panel of 187 countries and patents spanning 652 classes over 1978-2013.[19] This sample is modified in some specifications as described below. Finally, in order to construct a stock of patents K in i, c, t, we add up the flow of patents applying a 20% depreciation rate.[20] Figure 1 illustrates the distribution of

[16]Since we either use those patents registered in the EU or in the US, not the set of these, we have no issues regarding double counting in a patent family.

[17]In particular, patent boxes that reduce the income generated via patents is found to be a significant determinant of where multinationals locate patents. See, for example, Alstadsaeter, et al. (2018), Griffith, Miller, and O'Connell (2014), and Karkinsky and Riedel (2012). That said, the evidence of Akcigit, Baslandze, and Stantcheva (2016) suggest that superstar inventors are somewhat mobile, particularly within multinational firms.

[18]Patents are classified using the Cooperative Patent Classification (CPC) scheme.

[19]Note that in the estimations we drop country-class and country-year dyads for which there is no patenting activity since we include fixed effects for these two dyads.

[20]This is comparable to what is done in Coe and Helpman (1995), Keller (2002), and others.

patents across our sample of countries. As one would expect, larger, more developed economies patent more with the US as a particular leader. Figure 2 does so just for Europe where the same is found.

Figure 1: The Global Stock of Patents 1978-2013

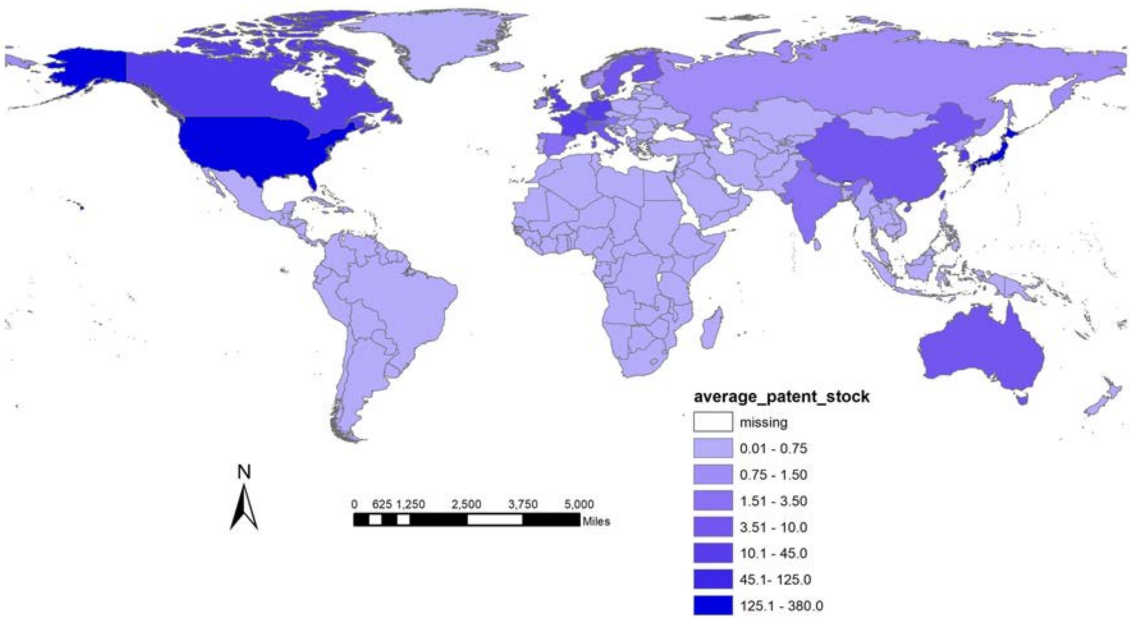
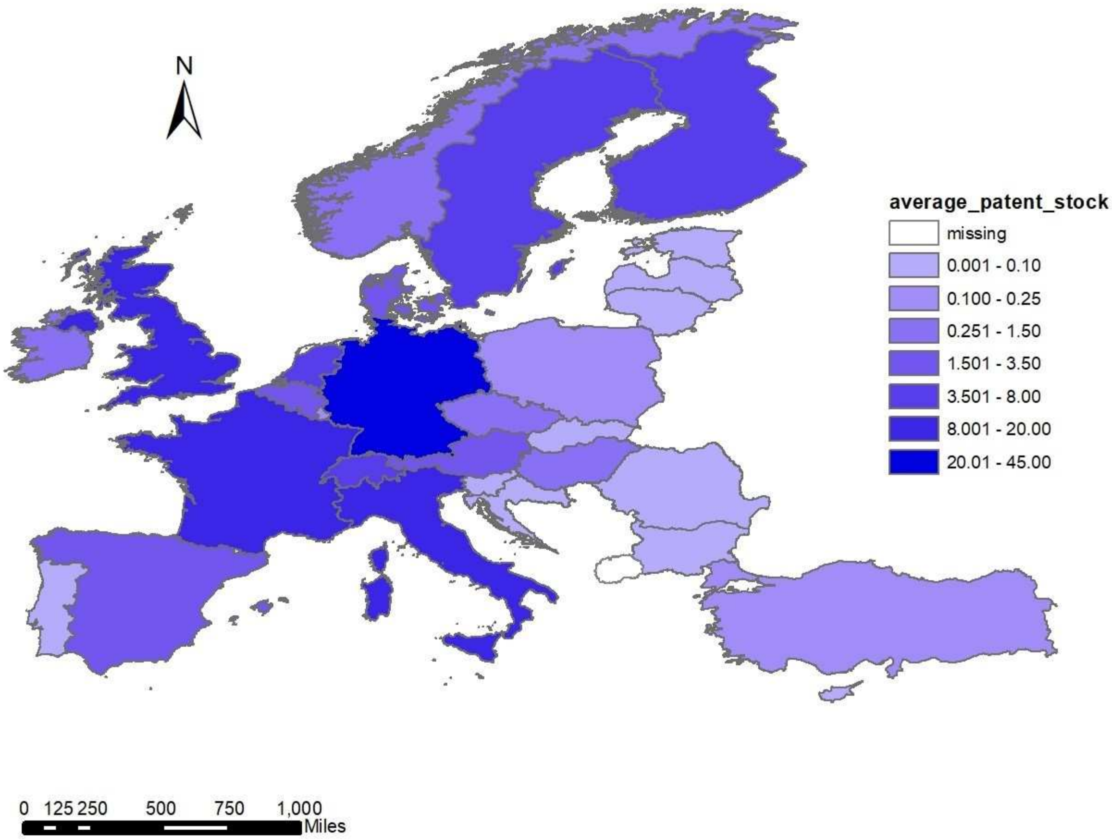


Figure 2: The European Stock of Patents 1978-2013



Our main control variables are those describing the linkages between innovation activity in country i and activity elsewhere. In particular our focus is on three import-related variables: import competition ($Comp_{i,c,t}$), diffusion ($Diffuse_{i,c,t}$), and imported inputs ($Input_{i,c,t}$). For each of these, we begin with the UN's Comtrade data at the most disaggregated level (six digits, or five digits for data before 2003).[21] To obtain the finest possible product information while keeping the highest available country coverage, trade data for different periods are collected using different trade classifications: SITC Rev.1 (until 1979), SITC Rev.2 (from 1980 to 1992), SITC

[21]These can be found at `https://comtrade.un.org/`.

Rev.3 (from 1993 to 2002), HS2002 (from 2003 to 2008) and HS2007 (from 2009 to 2013). Following that, we convert the product data to technology class data using the concordances of Lybbert and Zolas (2014) between the four digit CPC classification and each trade classification. Lybbert and Zolas (2014) develop this mapping by using text mining and a clustering algorithm to match between the text of a product description and the text of patents (including titles and abstracts). Although theirs is not the first attempt to generate such a mapping (with Schmookler (1966) providing one of the first), this methodology has a flexibility that vastly improves the matching of products and patents.[22] Although we refer the reader to their paper for details, a simple example here aids interpretation. Suppose that a given product p's description is found to match 140 patents, 50 in class A and 90 in class B. Their approach would then assign $\frac{50}{50+90} = 36\%$ of the product to class A and the remainder to B.[23] We then use this as the share of product p assigned to class c, given by $\tau_{p,c}$.

Import competition is then defined as:

$$Comp_{i,c,t} = \sum\nolimits_p \sum\nolimits_{j \neq i} \frac{M_{p,i,j,t}\tau_{p,c}}{GDP_{i,t}} \tag{4}$$

that is, country i's total imports in class c in a given year. Following the lead of van Pottelsberghe de la Potterie and Lichtenberg (2001), this is normalized by the size of i's economy since the same level of imports likely has a larger impact on competition in a small country rather than a large one.[24] As discussed in Section 2, the impact of this is theoretically ambiguous.

[22]Other contemporary concordances such as Van Looy, Vereyen and Schmoch (2014), which only allows for 44 technology classes or Dorner and Harhoff (2018), which considers only German patents, employ alternative methodologies. However, given the level of technology class aggregation and/or country coverage, these are unsuitable for our purposes.

[23]Their actual procedure is more complex in that it also accounts for the specificity of technology classes.

[24]Imports and GDP are measured in constant 2011 US dollars, with GDP coming from the World Development Indicators, available at `http://wdi.worldbank.org`.

In comparison, diffusion accounts for the ideas embodied in those imports. With this in mind, our measure of diffusion is:

$$Diffuse_{i,c,t} = \sum_p \sum_{j \neq i} \frac{M_{p,i,j,t} \tau_{p,c,t} K_{c,j,t}}{GDP_{i,t}} \tag{5}$$

where K_c, j, t is the stock of patents in country j in class c. The intuition for this variable is that the same imports from a country on the technological frontier (i.e. with more patents) does more to spark additional innovation in the importer than when those imports come from a laggard nation. Here, we anticipate a positive coefficient since the larger the technology content of imports, the larger the giant's shoulders on which a given country's inventors can stand. Figure 3 illustrates which countries where diffusion is largest. As with the location of patents, more developed countries tend to have more exposure to overseas patents. Two countries, however, deserve particular mention: China and India. The large exposure to overseas innovation for these countries is due to their particular place in global value chains where, by virtue of their processing of imports from developed countries (generally for re-export) they are especially poised for positive diffusion effects.[25]

Figure 4 does so for Europe.

[25] See Antras and Chor (2017) for a discussion of countries' places in global value chains.

Figure 3: The Technological Content of Imports

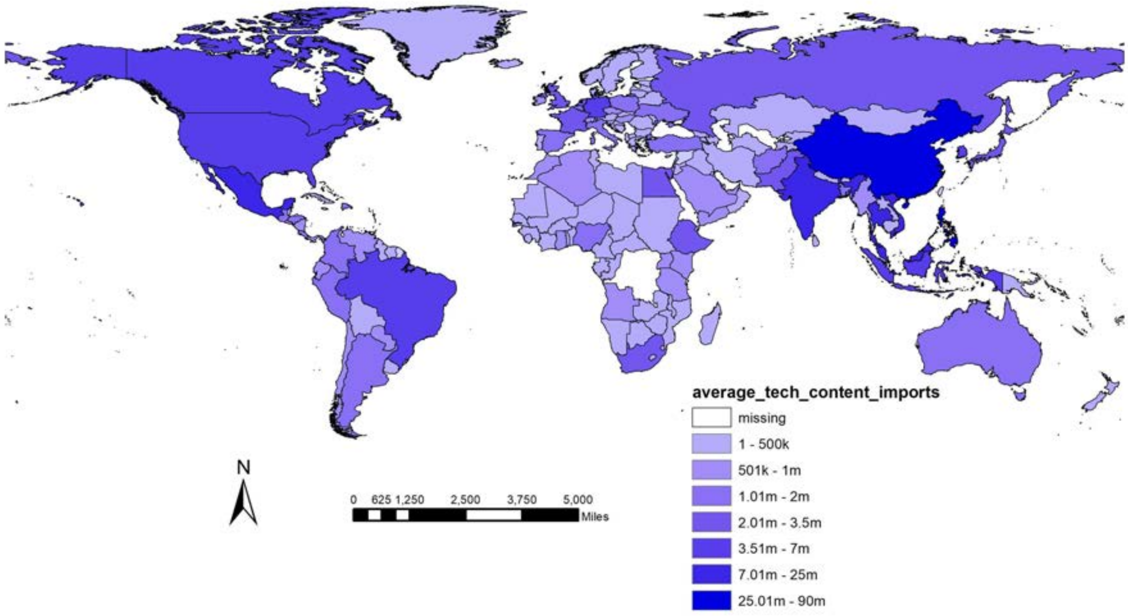
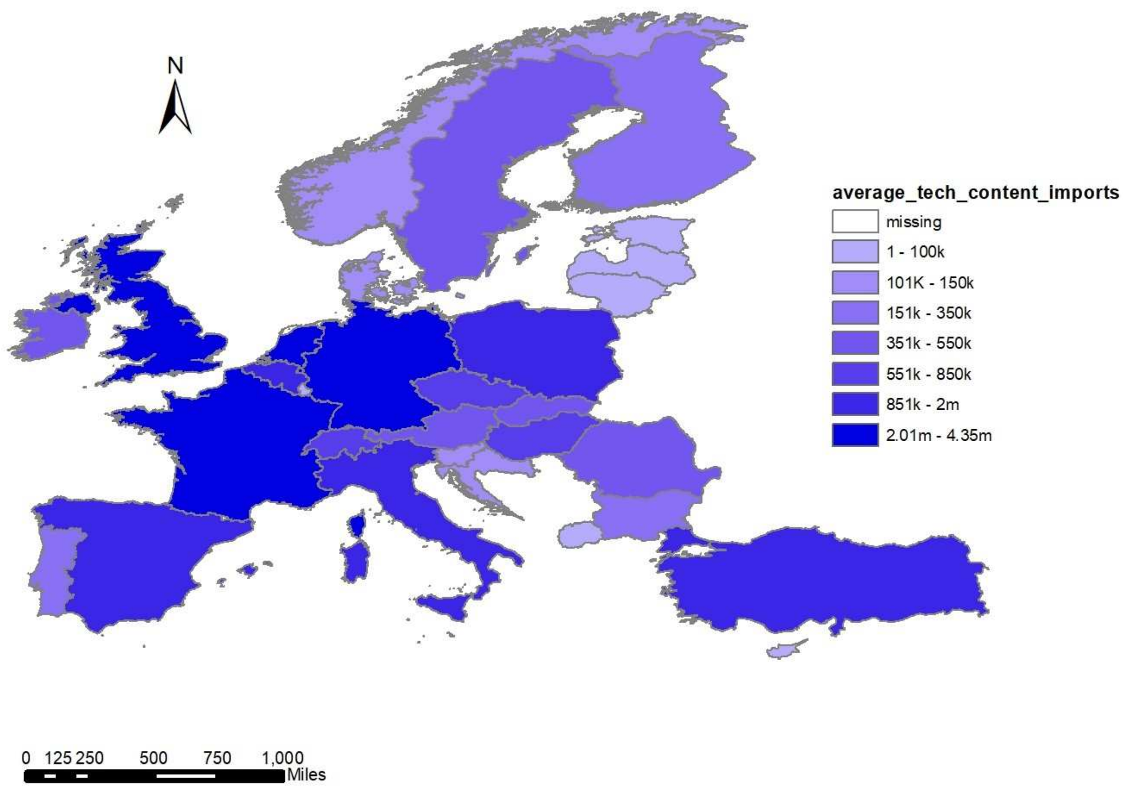


Figure 4: The Technological Content of European Imports



In addition to the import-driven diffusion measure, we include two additional controls measuring exposure to overseas innovation. The first is:

$$Social_{i,c,t} = \sum\nolimits_{j \neq i} \frac{S_{i,j,c} K_{j,c}, t}{S_i} \tag{6}$$

where $S_{i,j,c}$ is the number of patents in c sharing inventors in both i and j and S_i is the number of cross-border inventions in i. This measure captures the frequency of collaborations between i and j, with the presumption that more collaboration implies greater diffusion, particularly when there is more innovation in c in country j. Second, we use:

$$Dist_{i,c,t} = \sum\nolimits_{j \neq i} \frac{K_{j,c,t}}{D_{i,j}} \tag{7}$$

which is the distance-weighted sum of patents elsewhere. Following Keller (2002) among others, we weight by the distance $d_{i,j}$ between capital cities, taking our data from CEPII.[26] As discussed in Keller (2002) and others, distance is generally a significant barrier to international innovation spillovers with Keller (2002) estimating that the half-life of the effect at a mere 162km. Therefore although we anticipate the potential for a positive effect, we do not expect it to be large given the use of country-level data.

For the imported input variable, we follow Bloom, Draca, and van Reenen (2016) and employ input-output tables in order to allocate imports into those used as intermediates. Specifically, we use the 2016 revision of WIOD database which provides an input-output table for 39 countries across 56 sectors from 2000-2014.[27] From this we construct the share of imports that country i uses as inputs from country

[26]These can be found at `http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp`.
[27]This can be found at `http://www.wiod.org/`.

j's sector r in year t, denoted by $S_{i,j,r,t}$. For a given product p in sector r, we then assume that imported inputs are valued at $S_{i,j,r,t}M_{p,i,j,t}$.[28] Then, weighting this by the share of product p attributed to technology class c and multiplying by the j's stock of patents, for year t the input variable is:

$$Input_{i,c,t} = \sum_{p}\sum_{r}\sum_{j\neq i} \frac{S_{i,j,r,t}M_{p,i,j,t}\tau_{p,c}K_{c,j,t}}{GDP_{i,j,r,t}}. \tag{8}$$

As before, this is normalized by the size of the economy. Note that relative to PATSTAT the WIOD database is limited in time and country coverage. Therefore when we use this variable, we recalculate all other variables in order to maintain consistency across them. An additional caveat to the trade diffusion and input variables is that they presuppose a correlation between the source of an innovation (the location of inventors) and where it is applied (the source of imports). Alternatively, suppose that innovation is achieved in country k but applied in some other country j, meaning that the innovation originating in k is incorrectly assigned to imports from k rather than j. If this is the case, our results for the diffusion and input effects would be biased downwards. This is not the case for import competition, however, since that does not rely on the location of foreign innovation.

In addition to these five variables controlling for exposure to economic and innovation activity in other countries, we include the lagged stock of patents in country i in class c. This controls for, among other things, both persistence and learning by experience among a country's researchers. Finally, we include country-year and country-class fixed effects. The first controls for, among other things, country size (GDP; population), income levels, technological absorptive capacity, education, and geographic location. The latter would control for advantages in a particular class which, alongside the lagged dependent variable, should absorb other factors driving

[28] Thus, we assume that the share of imports that are inputs are the same for all p in a given s, although this can vary by exporter and year.

innovation in a given country and technology class. In some specifications, we further expand on the set of fixed effects to include year-class fixed effects that would control for common shocks across countries (such as a wave of innovation in a particular technology). Finally, excepting our fixed effects, our control variables are lagged at least one period in order to deal with possible endogeneity, with the length of lag explored below.

Table 1 provides summary statistics of the baseline variables included in the estimations.

Table 1: Summary Statistics

Variable	Observations	Mean	Sd. Dev.	Min	Max
$Patents_{i,c,t}$	822,043	3.44426	41.06532	0	6428.877
$K_{i,c,t-1}$	822,043	14.63885	167.9075	0	26228.33
$Diffuse_{i,c,t-1}$	822,043	4558471	1.44e+08	0	3.55e+10
$Comp_{i,c,t-1}$	822,043	16780.68	263696.5	0	9.42e+07
$Social_{i,c,t-1}$	822,043	.234755	7.566557	0	1800.824
$Dist_{i,c,t-1}$	822,043	.1614445	.3881974	.000407	47.88303
$Input_{i,c,t}$	156,319	828212.5	1.96e+07	0	2.61e+09

Given the large number of zeros and skewed nature of the distribution of patents across countries and classes, we estimate our model using a poisson estimator. In particular, given the large number of fixed effects, we implement the routine of Guimaraes and Portugal (2010). Note that our controls are in logs, however, since we take the log of sums, not the sum of logs, there are few problems with arising from the log of zero. In order to retain these problem cases, we include a dummy variable for each control variable where, when the control would be missing due to the log of zero, we replace the missing value with zero and set the dummy equal to one. The value in this approach is that it results in a specification which gives the estimated coefficients a quasi-elasticity interpretation. Finally, we cluster the robust standard errors at the class-year level.

4 Results

We present our baseline results in Table 2 where we experiment by including different combinations of the key variables. Note that, for the moment, we do not include the imported input variable as that limits the time and country dimension of our sample. Regardless of which set of controls we use, we include the lagged stock of patents which has a stable and significantly positive coefficient. This is then a strong indication that past successes in a technology class (and the variables underlying those) tend to point towards future successful innovation in the same class.

In column (1) to (4), we include one of our measures capturing the influence of overseas activity at a time. As can be seen, doing so results in a significantly positive coefficient for diffusion, import competition, and the social spillover variable. This result for import competition is consistent with that found by Bloom, Draca, and van Reenen (2016) and Coelli, Moxnes, Ulltveit-Moe (2016). Distance, however, is insignificant and has a markedly smaller point estimate. Given the results of Keller (2002) suggesting that innovation spillovers evaporate swiftly with distance, this is not surprising.

One potential issue with these specifications, however, is that since these measures are correlated with one another, using them individually as has been done in other studies can result in an omitted variable bias. With this in mind, columns (5) to (7) always include diffusion but add in each of the other three measures in turn. When doing so, we find that the coefficient for import competition does indeed appear to suffer from such a bias as it switches from significantly positive to significantly negative. This is not the case for the social coefficient which, although it falls slightly, remains significantly positive. Distance, meanwhile, remains insignificant. In each case, however, the diffusion variable remains significantly positive. Finally, in column (8) we reach our preferred specification which includes all four of these measures. As can be seen, this points to a significantly positive spillover via diffusion and social

Table 2: Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$lnDiffuse_{i,c,t-1}$	0.0274***				0.0605***	0.0241***	0.0274***	0.0508***
	(0.00209)				(0.00351)	(0.00206)	(0.00209)	(0.00347)
$lnComp_{i,c,t-1}$		0.0146***			-0.0451***			-0.0362***
		(0.00250)			(0.00432)			(0.00426)
$lnSocial_{i,c,t-1}$			0.0317***			0.0300***		0.0285***
			(0.00138)			(0.00139)		(0.00139)
$lnDist_{i,c,t-1}$				-0.000822			-0.000983	-0.00108
				(0.00191)			(0.00194)	(0.00196)
$lnK_{i,c,t-1}$	0.779***	0.797***	0.756***	0.800***	0.763***	0.740***	0.779***	0.729***
	(0.00643)	(0.00634)	(0.00644)	(0.00638)	(0.00658)	(0.00647)	(0.00643)	(0.00668)
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-Class FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	822,043	822,043	822,043	822,043	822,043	822,043	822,043	822,043

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

connections but a significantly negative one from import competition. This suggests that the innovation enchancing competition effects identified by Bloom, Draca, and van Reenen (2016) and others may instead be capturing a positive diffusion effect. Looking to the magnitudes of the coefficients and recalling the specification of the estimating equation, the results suggest that a 10% increase in the diffusion variable in year t would result in a 0.51% increase in the number of patents the following year. Note that this is only the short run effect since that rise in patents would increase the stock of patents and continue to indicate a rise in innovation in subsequent years. If import competition, on the other hand rises by 10%, this would imply a 0.36% short-run reduction in the number of patents. Social interactions, meanwhile, have the smallest point estimate so that a comparable increase only points to a 0.29% rise in innovation. Finally, note that once diffusion and import competition are jointly controlled for, the size of the estimated coefficients remain stable. Thus, while our results suggest an overall positive net effect from international trade, this is the result of conflicting diffusion and import competition forces.

4.1 Subsamples of the Data

Next, we proceed by investigating differences across subsamples of the data. Table 3 begins by considering eight different broad technology groups. As can be seen, the results are broadly consistent across the different categories. Beginning with diffusion, in each case we find a significantly positive coefficient, albeit one that is smaller for Physics and Electricity than for Fixed Constructions where a 10% rise in diffusion would lead to a 1.22% rise in new patents. Import competition has a negative point estimate across all eight groups, and one that is significant for all but Textiles and Paper and Physics. Comparable to diffusion, the social spillover variable is significantly positive in each case with Chemistry and Metallurgy patents particularly benefitting from cross-border collaborations. Distance, meanwhile, again remains

Table 3: Technology Group Subsamples

	(1) Human Necessities	(2) Perf. Op; Transport.	(3) Chemistry Metallurgy	(4) Textiles; Paper	(5) Fixed Constructions	(6) Mechanical Engineering	(7) Physics	(8) Electricity
$lnDiffuse_{i,c,t-1}$	0.0665***	0.0707***	0.0469***	0.0560***	0.122***	0.0908***	0.0281***	0.0205***
	(0.00807)	(0.00585)	(0.00935)	(0.0123)	(0.0132)	(0.00749)	(0.00783)	(0.00721)
$lnComp_{i,c,t-1}$	-0.0692***	-0.0629***	-0.0217**	-0.00791	-0.134***	-0.0557***	-0.0157	-0.0206**
	(0.00909)	(0.00667)	(0.00980)	(0.0176)	(0.0144)	(0.00826)	(0.00968)	(0.00861)
$lnSocial_{i,c,t-1}$	0.0239***	0.0199***	0.0458***	0.0192***	0.0216***	0.0210***	0.0245***	0.0247***
	(0.00332)	(0.00233)	(0.00379)	(0.00538)	(0.00458)	(0.00252)	(0.00380)	(0.00299)
$lnDist_{i,c,t-1}$	0.000481	-0.00601**	0.0108*	-0.00770	-0.00170	0.000770	0.00105	-0.00140
	(0.00381)	(0.00283)	(0.00636)	(0.00794)	(0.00648)	(0.00374)	(0.00479)	(0.00300)
$lnK_{i,c,t-1}$	0.667***	0.633***	0.600***	0.505***	0.487***	0.574***	0.805***	0.765***
	(0.0124)	(0.0103)	(0.0141)	(0.0192)	(0.0167)	(0.0110)	(0.0153)	(0.0121)
Observations	110,816	191,619	112,363	32,175	34,474	109,376	95,393	67,831
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-Class FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

largely insignificant with the only significantly positive coefficient being found for Chemistry and Metallurgy. Finally, as expected, past success predicts current innovation across all the groups. Thus, Table 3 indicates that our results are not driven by any one class but rather that the findings in the full sample hold true even when allowing the effects to vary across technology groups.

Table 4 recombines across technology groups but splits the sample along countries. In column (1) we include only OECD importers whereas column (2) includes only non-OECD countries. Note that for both, our variables are the same as in Table 2, i.e. diffusion is that from all sources, import competition is that from all imports, and so on. The reason for this sample split is two-fold. First, as noted in Section 3 patenting activity is highly skewed with the majority of patenting activity is carried out by OECD countries.[29] As such, including developing countries with low innovation levels can exacerbate the skewness and throw off the estimates. Second, the impact of international exposure can vary according to a country's level of development. For example, the ability to benefit from diffusion may be contingent upon absorptive capacity (something explored further below). Furthermore, the theory suggests that the impact of import competition can depend on the degree of competition and the quality differential of imported goods compared to local production, factors which may vary with local development. Comparing the results across the two columns, we see a broadly similar pattern with one exception: import competition. In OECD countries, import competition is significantly negative in line with the full sample estimates. Non-OECD countries, however, find that import competition exerts a significantly positive effect on local innovation. This would be consistent with imports marginally reducing market size in developed countries where the local technological level is fairly high but nearly eliminating it in low-technology developing countries forcing local firms to innovate in order to survive at

[29]This can be seen by the fact that, despite the fact that only 36 of our 187 countries are in the OECD, the OECD countries make up 62% of the observations, something that occurs because due to the fixed effects we exclude country-classes and country-years for which there is no patenting.

all. A final point of interest is in the lagged patent stock variable results. Although it is significantly positive for both country groups, it is noticeably larger for the OECD countries. This suggests that success is more likely to build on success there than in developing countries.

Table 4: OECD versus Non-OECD Subsamples

	(1) OECD	(2) non-OECD
$lnDiffuse_{i,c,t-1}$	0.0482***	0.0500***
	(0.00369)	(0.00870)
$lnComp_{i,c,t-1}$	-0.0369***	0.0414***
	(0.00452)	(0.00956)
$lnSocial_{i,c,t-1}$	0.0266***	0.0390***
	(0.00140)	(0.00642)
$lnDist_{i,c,t-1}$	-0.00118	0.00157
	(0.00205)	(0.00639)
$lnK_{i,c,t-1}$	0.752***	0.495***
	(0.00710)	(0.0117)
Observations	550,729	271,314
Country-Year FE	YES	YES
Country-Class FE	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5 instead cuts the time period in half with column (1) looking at 1978-1994 and column (2) running from 1994 until 2013. Note that although this is an even split in terms of the years, the number of observations is nearly twice as large in the post-1993 sample of column (2). This is due to the increased innovative activity after that point, meaning that fewer country-class or country-year dyads are dropped due to lack of variation. Comparing across columns, we find three things. First, the overall pattern of coefficients is stable across the two time periods and both match that found in the baseline results. Second, the point estimates for diffusion and import competition are lower post-1993, suggesting that innovation may be becoming less

Table 5: Time Period Subsamples

	(1) pre-1994	(2) post-1993	(3) post-1993
$lnDiffuse_{i,c,t-1}$	0.0979***	0.0475***	0.0496***
	(0.00530)	(0.00597)	(0.00561)
$lnComp_{i,c,t-1}$	-0.0742***	-0.0332***	-0.0378***
	(0.00626)	(0.00691)	(0.00663)
$lnSocial_{i,c,t-1}$	0.0175***	0.0306***	0.0290***
	(0.00193)	(0.00201)	(0.00196)
$lnDist_{i,c,t-1}$	0.000607	-0.000533	8.67e-05
	(0.00256)	(0.00231)	(0.00218)
$lnK_{i,c,t-1}$	0.399***	0.597***	0.581***
	(0.0108)	(0.0104)	(0.0106)
Observations	238,153	462,115	462,115
Country-Year FE	YES	YES	YES
Country-Class FE	YES	YES	YES
Class-Year FE	NO	NO	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

influenced by trade-induced linkages. The reverse is true for the social variable, however, suggesting a rising importance of cross-border collaborations. In an era where the mobility of researchers is under threat by immigration policy changes in the US, the UK, and elsewhere, this suggests the potential need for particular diligence in maintaining international research networks. Finally, the coefficient on the lagged patent stock is roughly 50% higher in the latter half of the sample. This suggests that in the latter half of the data, that there may be increased specialization with an increasing majority of innovations in a particular class taking place in those countries that have been traditional leaders in the area. Finally, column (3) adds class-year fixed effects to the post-1993 subsample.[30] The value in this is that it allows for changes across time for a given class which is common to all countries (such as the rise in focus on a particular research area). Further, it allows us to tighten identification since it increases the within-ness of our analysis since the comparision is now to other years in the same class as well as within a country over time and within a country across classes. That said, including these does not fundamentally alter our basic results: diffusion and international collaboration increase innovation whereas import competition reduces it.

4.2 Patent Quality

Up to this point, we have used all patents, however, this presupposes that the knowledge content of all patents is the same. An alternative is to use some proxy of patent quality. One common one is forward citations as was used by Bloom, Draca, and van Reenen (2016). An alternative, and the one we pursue alongside Coelli, Moxnes, Ulltveit-Moe (2016) is to use the size of the patent family. Specifically, we reconstruct all of our variables but only use pentadic patents, that is, those patents

[30]Recall that with 652 classes, doing so for each year introduces an equal number of fixed effects that needed to be estimated. As such, doing this for just this 20 year period adds 13,040 fixed effects which proved infeasible to include in the full sample.

Table 6: Pentadic Patents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$lnDiffuse_{i,c,t-1}$	0.0466***				0.0635***	0.0342***	0.0478***	0.0421***
	(0.0107)				(0.0209)	(0.00990)	(0.0100)	(0.0160)
$lnComp_{i,c,t-1}$		0.0347***			-0.0296			-0.0116
		(0.0131)			(0.0262)			(0.0216)
$lnSocial_{i,c,t-1}$			0.0625***			0.0598***		0.0599***
			(0.00800)			(0.00779)		(0.00687)
$lnDist_{i,c,t-1}$				0.00515			0.00549	0.00510
				(0.00351)			(0.00351)	(0.00345)
$lnK_{i,c,t-1}$	0.226***	0.234***	0.184***	0.237***	0.225***	0.179***	0.227***	0.179***
	(0.0274)	(0.0279)	(0.0253)	(0.0276)	(0.0266)	(0.0251)	(0.0274)	(0.0252)
Observations	267,401	267,401	267,401	267,401	267,401	267,401	267,401	267,401
Country-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Country-Class FE	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

which made applications to the US, EU, Japanese, Korean, and Australian patent offices (those for which we have data). Given the cost of patenting, this should restrict patents to just those of higher quality. Note that, as compared to similar estimations with USPTO data[31], relying on pentadic data considerably reduces the number of patents used and, as noted in the subsamples above, this can result in a lack of variation in country-class and country-year dyads which lowers the number of observations.

In Table 6 we use these alternatives to repeat Table 2.[32] In columns (1) to (4), we again include our international variables one at a time, arriving at comparable conclusions as before, i.e. diffusion, import competition, and social interactions all increase innovation. That said, as found in column (5), the positive import competition variable is biased because of the omitted diffusion variable. Once both are included, import competition becomes negative, although insignificantly so. This is not the case, however, for the social (column (6)) or distance measures (column (7)). Finally, when all of the variables are included at once, we find a sign pattern consistent with the comparable column in Table 2, although import competition remains insignificantly negative. Furthermore, note that in comparison to Table 2's column (8) the coefficient for diffusion is only marginally smaller whereas that on the social measure is actually larger, suggesting that diffusion among high-quality patents may be especially important.

4.3 Alternative Lags

Up to this point, we have only included the $t-1$ values of our control variables. In Table 7 we alter this by including longer lags. In column (1), we begin by

[31] These estimations provide very stable results as compared to the baseline estimations Table 2. They are unreported in the current report, but are available upon request.

[32] In unreported results, we also repeat the above subsamples for this group of patents. Largely comparable results were found and are available on request.

Table 7: Alternative Time Lags

	(1)	(2)	(3)
$lnDiffuse_{i,c,t-1}$	0.0430***		
	(0.00581)		
$lnDiffuse_{i,c,t-2}$	0.00248		
	(0.00603)		
$lnDiffuse_{i,c,t-3}$	0.00553	0.0294***	
	(0.00449)	(0.00425)	
$lnComp_{i,c,t-1}$	-0.0355***		
	(0.00526)		
$lnSocial_{i,c,t-1}$	0.0222***		
	(0.00168)		
$lnDist_{i,c,t-1}$	0.00244		
	(0.00230)		
$lnComp_{i,c,t-3}$		-0.00996*	
		(0.00521)	
$lnSocial_{i,c,t-3}$		0.0109***	
		(0.00157)	
$lnDist_{i,c,t-3}$		-0.00252	
		(0.00222)	
$lnDiffuse_{i,c,t-5}$			0.0193***
			(0.00472)
$lnComp_{i,c,t-5}$			-0.00327
			(0.00578)
$lnSocial_{i,c,t-5}$			0.00257
			(0.00177)
$lnDist_{i,c,t-5}$			0.000846
			(0.00234)
$lnK_{i,c,t-1}$	0.751***	0.779***	0.785***
	(0.00746)	(0.00741)	(0.00829)
Observations	524,458	527,025	424,842
Country-Year FE	YES	YES	YES
Country-Class FE	YES	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

including the $t-2$ and $t-3$ lags of the diffusion variable. When doing so, we find that only the $t-1$ diffusion variable has a significant effect on current patenting activity, with the other results the same as before. This raises concerns about the potential of endogeneity bias in which some underlying short-run variable not captured by the country-year and country-class fixed effects is correlated with both current patenting and the diffusion variable's most recent lag. To this end, column (2) instead uses only the $t-3$ lags of all the control variables (excepting the lagged stock of patents). This longer lag should eliminate endogeneity problems arising from a short-run variable. When doing so, we find a pattern of coefficients that is the same as what is found in the baseline results where we use the $t-3$ lags. That said, the magnitude of the coefficients is somewhat smaller and, especially for import competition, significance is lower. In column (3), we push this further by using the $t-5$ lags of our innovation spillover variables. Now, although the pattern of coefficient signs remains the same, only the diffusion variable is significant, where it is positive as before. This suggests two things. First, the inspirational effects of diffusion act quickly with the most recent exposure to overseas innovation having the most significant impact. Second, since the pattern of results is robust to using longer lags, this argues against endogeneity driving the results.

4.4 The Role of TRIPS

In our analysis, the underlying notion has been that imports embody the technology of the exporting nation as represented by its patents. This, however, need not be true since innovators can continue to send prior, less-advanced versions of their products as opposed to those using the latest patented technologies.[33] One reason for doing so is over concerns about the protection of patents in the importing country. Smith (2001) finds that stronger destination patent rights increase sales by US firms, sug-

[33] This may arguably apply more to product innovation rather than process innovation.

gesting that they withhold exports of sensitive products out of concerns about their ability to control their innovations. Similarly, McCalman (2001) finds that patent harmonization enabled the transfer of income to patent generating countries, the US in particular, further suggesting that increasing destination intellectual property right protection (IPR) increases the willingness to export products embodying the most recent innovations.

Table 8: The Impact of TRIPS

	(1)	(2)	(3) TRIPS	(4) Non-TRIPS
$lnDiffuse_{i,c,t-1}$		0.0858***	0.0689***	0.108***
		(0.0234)	(0.00677)	(0.00666)
$lnComp_{i,c,t-1}$		-0.0699**	-0.0601***	-0.0953***
		(0.0312)	(0.00808)	(0.00862)
$lnSocial_{i,c,t-1}$	0.0296***	0.0293***	0.0315***	0.0205***
	(0.00212)	(0.00212)	(0.00208)	(0.00197)
$lnDist_{i,c,t-1}$	0.00417*	0.00410*	0.00214	0.000264
	(0.00231)	(0.00231)	(0.00235)	(0.00279)
$lnDiffuse_{i,c,t-1}$ (from TRIPS)	0.0680***	-0.0124		
	(0.00648)	(0.0229)		
$lnComp_{i,c,t-1}$ (from TRIPS)	-0.0544***	0.00958		
	(0.00838)	(0.0316)		
$lnK_{i,c,t-1}$	0.563***	0.559***	0.562***	0.447***
	(0.0110)	(0.0110)	(0.0108)	(0.0114)
Observations	394,541	394,541	415,537	286,724
Country-Year FE	YES	YES	YES	YES
Country-Class FE	YES	YES	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

One way in which countries are able to signal their IPR strength is by participating in the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), which ensures IPRs for firms from other World Trade Organization (WTO) members. Commencing in 1995 for most WTO members, with other continuing after, if TRIPS is a convincing signal of IPR protection this might lead to an increase in the innovation content of trade, generating greater spillovers. We explore this in Table 8 by calculating diffusion and import competition using only imports for TRIPS countries. In column (1), we include only this measure, i.e. assuming no trade-related spillovers for non-TRIPS nations, and find comparable results to our baseline. In column (2), however, do not make this assumption and find no significant differences between TRIPS and non-TRIPS countries. In columns (3) and (4), we instead separate the sample into TRIPS importers and non-TRIPS importers. As can be seen, the pattern of coefficients is largely the same, although the point estimates are noticeably higher for TRIPS countries. Nevertheless, we do not find a significant difference in international innovation spillovers from TRIPS participation. It should, however, be noted that this may be due to the fact that most countries in the data began TRIPS at the same time. Given our country-year fixed effects, this may leave relatively little variation for the data to pick up on.

4.5 Absorptive Capacity

As discussed in Table 4 there may be a difference across countries from the import competition variable due to differences in absorptive capacity. In this subsection, we consider this further by using a revealed technological advantage (RTA) measure adopted from the revealed comparative advantage of Balassa (1965). This RTA measure is:

$$RTA_{i,c,t} = \frac{K_{i,c,t-1}}{\sum_c K_{i,c,t-1}} \frac{\sum_j \sum_c K_{j,c,t-1}}{\sum_j K_{j,c,t-1}} \tag{9}$$

i.e. the share of patent stock in i in class c relative to the share of c in the global patent stock. If a country has an RTA greater than one, this class features more heavily in its patent mix than it does for the average country. That nation may therefore have greater absorptive capacity and a greater potential for international innovation spillovers. Table 9 tests this by splitting the sample between countries with an RTA in a given class (column (1)) and those without (column (2)). What emerges from this is a comparable pattern of coefficients across the two samples. That said, there are noticeable differences. In particular, country-class pairs with an RTA tend to experience greater international trade-related spillovers as well as suffer more from import competition. On the other hand, country-class dyads without an RTA tend to benefit more from social connections. In addition, here we find a positive spillover from distance-weighted innovation. Despite these differences, the picture is broadly the same across the two groups. Further, the notion that low absorptive capacity (low RTA) countries are find smaller negative effects from import competition is in line with the hypotheses discussed for the non-OECD countries in Table 4.

Table 9: Revealed Technological Advantage

	(1) With RTA	(2) Without RTA
$lnDiffuse_{i,c,t-1}$	0.0604***	0.115***
	(0.00512)	(0.00578)
$lnComp_{i,c,t-1}$	-0.0434***	-0.103***
	(0.00625)	(0.00667)
$lnSocial_{i,c,t-1}$	0.0286***	0.0402***
	(0.00185)	(0.00171)
$lnDist_{i,c,t-1}$	-0.000200	0.00443*
	(0.00271)	(0.00239)
$lnK_{i,c,t-1}$	0.646***	0.616***
	(0.0109)	(0.00752)
Observations	279,900	360,911
Country-Year FE	YES	YES
Country-Class FE	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.6 Imported Inputs

To this point, we yet to employ the imported input variable. This is because, in order to construct it, we were forced to employ the WIOD data which limited us in terms of country and year coverage. Here, however, we include it and acknowledge the limitations this imposes on the sample. Furthermore, note that we recalculate the control variables to include only the patents and imports in the countries in WIOD data.

Table 10: Imported Inputs

	(1)	(2)	(3)	(4)	(5)
$lnDiffuse_{i,c,t-1}$	0.0323***				
	(-0.00617)				
$lnComp_{i,c,t-1}$		0.0209***			
		(-0.0071)			
$Input_{i,c,t-1}$			0.0230***		
			(-0.00501)		
$lnSocial_{i,c,t-1}$				0.0333***	
				(-0.00296)	
$lnDist_{i,c,t-1}$					0.000545
					(-0.00304)
$lnK_{i,c,t-1}$	0.546***	0.561***	0.550***	0.523***	0.563***
	(-0.0197)	(-0.0201)	(-0.0193)	(-0.019)	(-0.0202)
Observations	156,319	156,319	156,319	156,319	156,319
Country-Year FE	YES	YES	YES	YES	YES
Country-Class FE	YES	YES	YES	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10 begins by again including each of the international linkages one at a time. We do this because these specifications match those of Table 2's columns (1) to (4), allowing us to examine what differences are generated by the smaller sample. Despite this difference, we find the same pattern as before for diffusion, import competition, social connections, and distance, namely that all but the last significantly increase local innovations. Furthermore, the size of the point coefficients does not differ dramatically from what was found in the full sample. This suggests that whatever differences are found are arguably not due to the change in sample. In column (3), we include the input variable on its own. As can be seen, when doing so it is positive and significant, a result reminicent of the findings of Goldberg, et al. (2010) and Colantone and Crino (2014). However, as indicated in the baseline results, these exercises may lead to misleading results due to omitted variable bias.

Table 11: Imported Inputs

	(1)	(2)	(3)	(4)	(5)	(6)
						Pentadic
$lnDiffuse_{i,c,t-1}$	0.0715***	0.0327***	0.0300***	0.0323***	0.0626***	0.0675***
	(-0.0113)	(-0.0094)	(-0.00604)	(-0.00616)	(-0.0124)	(0.0188)
$lnComp_{i,c,t-1}$	-0.0528***				-0.0464***	-0.0106
	(-0.0132)				(-0.0129)	(0.0250)
$lnInput_{i,c,t-1}$		-0.00041			0.00215	-0.0186
		(-0.00736)			(-0.00721)	(0.0152)
$lnSocial_{i,c,t-1}$			0.0322***		0.0314***	0.0581***
			(-0.00295)		(-0.00294)	(0.00729)
$lnDist_{i,c,t-1}$				0.000279	0.000762	0.00846**
				(-0.00308)	(-0.00308)	(0.00418)
$lnK_{i,c,t-1}$	0.530***	0.546***	0.508***	0.546***	0.495***	0.174***
	(-0.0191)	(-0.0196)	(-0.0187)	(-0.0197)	(-0.0181)	(0.0321)
Observations	156,319	156,319	156,319	156,319	156,319	141,787
Country-Year FE	YES	YES	YES	YES	YES	YES
Country-Class FE	YES	YES	YES	YES	YES	YES

Robust standard errors clustered by class-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

With this in mind, Table 11 mirrors the second half of Table 2 by including combinations of the variables, in particular diffusion which is significantly positive across the specifications. When doing this, we find that, as in the full sample, this leads to a significantly negative coefficient for import competition but does not markedly alter the estimates on social or distance. Comparable to the import competition variable, the input coefficient switches sign and becomes negative, albeit insignificantly so. This again suggests that the positive coefficient for inputs in Table 10 was misattributed from the diffusion effect. This holds when including all of the variables in column (5) and when using only the pentadic variables in column (6). Thus, the existing work suggesting a positive innovation effect from imported intermediates may benefit by simultaneously controlling for diffusion effects.

4.7 Technology Class Size

In the construction of our trade related measures, we controlled for the size of the importing country's GDP since the impact of a given exposure to foreign innovation likely has a differential impact in a small versus a large importer. This can be refined, however, by focusing more on the size of activity of a given class in that importer. To take the best feasible step in this direction, in Table 12 we again employ the WIOD data and, for each c belonging to a sector r, also control for the total sales (column (1)) or value added (column (2)) of r in i, t. As can be seen, these are not significant (perhaps due to the country-class fixed effects and the stability of these values over time) nor do they affect the conclusions drawn from the analysis.

Table 12: Alternative Size Measure

	(1)	(2)
$lnDist_{i,c,t-1}$	0.0630***	0.0629***
	(0.0132)	(0.0132)
$lnDist_{i,c,t-1}$	-0.0595***	-0.0595***
	(0.0120)	(0.0120)
$lnInput_{i,c,t-1}$	0.00635	0.00649
	(0.00931)	(0.00930)
$lnSocial_{i,c,t-1}$	0.0317***	0.0318***
	(0.00287)	(0.00287)
$lnDist_{i,c,t-1}$	0.00712**	0.00713**
	(0.00344)	(0.00344)
$lnSales_{i,c,t-1}$	-0.00469	
	(0.00404)	
$lnVA_{i,c,t-1}$		-0.00483
		(0.00396)
$lnK_{i,c,t-1}$	0.474***	0.475***
	(0.0178)	(0.0178)
Observations	128,506	128,504
Country-Year FE	YES	YES
Country-Class FE	YES	YES

Robust standard errors clustered by class-year in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

5 Final remarks and policy implications

The current project contributes to analyze the role of imports in diffusing technological knowledge and stimulating local innovation. By linking product-level import data and technology-level information, we show a new evidence of diffusion of ideas via the technological content of imported goods and find that exposure to overseas innovation via imports is the main driver of positive international innovation spillovers. We consistently find that the import-driven international innovation spillovers are mainly driven by the exposure to the technological content of imports, whereas import competition seems to play a negative role once the diffusion effect taken into account.

Our results point towards several policy implications. We find that importing goods with a high technological content spurs local innovation. This suggests that, to establish oneself in a technological field (something that then feeds further into future patenting activity) it is important not to simply open ones borders to imports overall, but to concentrate on encouraging trade from leaders in the area. This then points more towards implementing regional trade agreements than broad-based border opening (such as under the World Trade Organization). Furthermore, we find robust evidence that past international research collaborations promote current innovations. This argues against the current push against the international flow of skilled labour as embodied in policies such as Brexit. This also shed some further on the role of multinationals in the international diffusion of knowledge.

Our findings suggest that to encourage domestic innovation, it may be necessary not only to open one's borders but to seek out particular trade agreements with leaders in the technologies one hopes to work on. Second, in line with the concerns of Keller (2002), it points to the possibility that trade agreements among the world's technological leaders may lead to income divergence. Finally, the current political climate is one in which the trend is towards isolationism with technological leaders such as the US and the UK looking to close their borders to imports and immigration. Based on our estimates, this would have a cooling effect both for themselves and for their trading partners.

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