Import Competition, Destinations, and Firms’ Patent Strategies

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1. Introduction

International trade has undergone rapid changes in the last two decades. Eastern-European countries opened up and China joined the WTO. These and many other countries that initially played a minor role in international trade have now become major competitors of traditional industrial countries. As a response to such changes, firms have to find ways to remain competitive in the market. Recent research by Aghion et al. (2005), Autor et al. (2020), Bloom et al., (2016) considered innovation strategies as a response to this import competition where firms seek new opportunities in new developed technologies. However, little is known on how trade and the type of innovation are related to each other. Following the work of Liu and Rosell (2013), import competition may lead firms to more complex patents and then they are therefore better positioned to internalize any productivity gains.

In this paper, we explore how import competition from the rest of the world has affected firm-level innovation strategies in the Netherlands. Exposure to import competition, as a result to open markets, will lead to local firms facing fiercer competition. Markets become thinner because higher import competition means more entry of new products. More import competition causes to firms signals of either lower expected profits or higher expected costs that might hamper innovation. On the other hand, it might also push them to keep innovating to remain competitive (Bloom et al., 2016). The empirical evidence of recent papers remains mixed. Akcigit and Melitz (2021) note that "the ultimate direction for the impact of competition on innovation varies by country, industry, and across different types of firms and innovation efforts". Therefore, they develop a theoretical framework that includes several effects that are relevant for the links between trade and innovation. Some of those effects are import competition and domestic competition. Our analysis also includes those variables.

In this paper, we follow Aghion et al. (2005) and explain firm-level innovation activities using patent counts. If firms are innovative capable of expanding their competitive advantage, more competition (i.e. foreign imports forces firms to become more innovative) is a channel through which imports will likely impact their patent activity trajectories.

On the other hand, firms may also consider a strategy with unused patents. This can be to prevent other firms using the patented technology or to keep the patents for future production activities. According to models of rivalry related to the role of entry barriers raised by incumbent firms as a response to more competition, firms can use patent strategies to discourage entry by potential entrants (Belderbos and Somers, 2015). A primary strategy to raise such barriers is to obtain a strong position within a technology domain that reduces the technological opportunities of other firms.

One of the primary aims of this paper is to investigate the relationship between import competition and heterogeneous patent strategies. We use several measures of innovation based on patent data statistics. We distinguish between a firm's number of domestic and European patents to capture the innovation activities of not only the larger firms, but also of a large group of SMEs. In addition, we use the number of forward citations of a firm's patents which is informative about the intrinsic quality of patents (Harhoff et al., 1999). This allows us to discern the quantity versus the quality effect. A third measure of firms' technological activities is defined on the basis of "explorative" technological activities. Hereby firms can escape competition either by patenting in new technology classes and/or by relying on knowledge that is more geographical spread.

The most recent line of research (Bloom et al., 2013, 2016; Autor et al., 2020) focuses on the innovation impact of Chinese import exposure of US or Canadian domestic firms highlighting the impact of import competition from "low-wage countries" on firms in developed countries. But focusing on the European context, for instance, is relevant as well. Since one important premise of the Single Market Program has been to increase competition. Furthermore, it is estimated that in 2010, 10 percent of competing imports for the Dutch domestic market come from China and 64 percent from the EU. Therefore, our analysis extends import competition for a firm also to imports from high-wage countries. So far, the literature finds little empirical evidence on the effect of increasing trade integration on innovation in high-wage countries. Our data allows us to distinguish import competition from various income-level countries that could also have varying impact on innovation.

In summary, the main contribution of this paper to the literature is the following. We show not only that import competition positively impacts the number of patents, but also positively impacts the quality of these patents. We consider different origins of the import competition and show that it matters. Furthermore, we show that SMEs have a similar response to increased import competition as large enterprises.

Note that there is also a novelty in the way this paper puts attention to measurement. We slightly distress from the approach of Autor et al. (2020) and Chakravorty et al. (2017) in measuring import competition and do not use trade and industry data, but use data from National Accounts about imports, exports and turnover at the industry level. The advantage of data of

National Accounts is that the underlying data sources are integrated on industry level and that time series have been constructed that avoid methodological changes and changes of classifications. In addition, the National Accounts data enables us to solve the problem of trade in goods considered for re-exports. This is necessary since about half of Dutch trade in goods consider re-exports, who do not form competition for sales on the domestic market.

To assess the impact of import competition on innovation, we consider a panel of firms located in the Netherlands with annual data from 2000-2010. The variables include general business demography information such as size, industry and ownership, and include R&D expenditure, patent application counts and forward citations of these patent applications as well. Our sample departs from a population that includes (almost) all firms located in the Netherlands that during the period 2000-2010 applied for one or more patents at the European Patent Office. The firms in our sample are enterprise groups located in the Netherlands, but not necessarily the ultimate parent firm since foreign control is possible. The statistical unit "enterprise group" is essential in the construction of a patent sample, because firms may register patents (and R&D) under different names. Generally speaking, the ownership of a patent occurs at the level of an enterprise group and it is practically impossible to link this ownership to affiliates or plants. For example, it is Philips that owns a patent and not the plant where the corresponding invention was made. Note that in this way, we study the effects of domestic import competition on domestic innovation. We do not study the effects of domestic import competition on the worldwide innovation of enterprises with a plant in the Netherlands, nor do we study the effects of worldwide import competition on the domestic innovation of enterprises with a plant in the Netherlands. For a multinational, import competition and innovation can take place in different countries. Liu and Uzunidis (2021) note that in the 1980's relocation of R&D activities was only to adapt the product to the local market, but that during the years, R&D activities of firms were more and more globally integrated.

To address econometric concerns about possible state dependence and time-invariant unobserved firm-level heterogeneity, we control for random effects applied to count data using the Wooldridge (2005) estimator approach. To account for unobserved time-varying factors which affect both the firm's innovation output and import competition we rerun our main regression using a general method of moments (GMM) estimation where we instrument import competition variable.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature. Section 3 describes data, whereas section 4 presents the empirical model. In

Section 5 we present the estimation results and section 6 contains several robustness checks. Finally, Section 7 concludes.

2. Literature Review

2.1. Competition and innovation

Theoretically, rising competition has an ambiguous effect on innovations. This can be reconciled with the model of innovation put forward by Aghion et al. (2005) who present a theory known as the inverted U or bell-shaped theory reconciling the Schumpeterian (Schumpeter 1934) and the escape-competition conflicting theories. According to this theory, the relationship between the level of competition and innovation is dependent on the initial level of competition. The expected impact of exposure to trade openness on the innovation incentives of domestic firms can also be reconciled with the such theoretical prediction from which no clear consensus can be made. In an open economy, the usual presumption embedded in models is that of a trade shock which captures some form of trade liberalization (lower tariff and/or non-tariff barriers). The move to a more open economy puts firms in import-competing industries under pressure because it signals either lower expected profits or higher expected costs from more reliance on external financing (Bloom et al., 2016). In a duopolistic model, the authors assume two markets: a leveled market wherein two firms highly compete at equal levels of innovation and an unleveled market that consists of an innovation leader firm and an innovation follower firm (laggard). Given this framework, the inverted U-shape is explained as follows. At an initial low level of competition, firms in the leveled market will have low innovation incentives and any increase in competition should result in higher innovation incentives. In this situation, the market is characterized by a dominating escape-competition effect on the follower to innovate because the difference between being a leader or a follower intensifies. On the other hand, at an initial highly competitive level, the innovation incentives of the follower are low because his profits are zero anyways.

The papers of Bloom et al. (2013, 2016, 2021) provide some guidance about the impact of low-cost import competition on innovation. The authors reconcile some theoretical considerations with micro-empirical evidence showing that more import competition from low-wage countries, such as China, lead firms to increase their innovation activities. They explain this apparent puzzle by developing a 'trapped factors' model of the firm where it would rather redeploy productive resources to innovation. That is, productive resources are 'trapped' inside the firm and, as a within firm-effect, these factors can easily, at a lower cost, be used for innovation. Greater import competition therefore may lead to higher patent activities at the level of the firm. At a more aggregated level, Bloom et al. (2016) look also at an intra-firm allocation whereby import shocks might induce a reallocation of resources toward the more technologically advanced firms. This indirectly boosts resource allocation to innovation activity. These results are also in line with those of Arora et al. (2015) who find a positive relationship between import competition and patenting in their correlational analysis.

The empirical evidence from recent papers remains mixed. Bloom et al. (2016) use panel data across 12 European countries from 1996-2007. The authors provide evidence that not only the number of patent applications rose but that also TFP, IT intensity, R&D expenditure and quality of management practices increased in firms which were more exposed to Chinese import competition. In addition, the authors also found evidence that increased Chinese import competition reallocated employment toward more technologically advanced firms. Similarly, Coelli et al. (2022) consider the impact of trade liberalization on patent applications. They find greater patenting and they see import competition as the cause.

These results, however, are in contrast with Autor et al. (2020). These authors provide evidence on how US firms respond to import competition from China. Their analysis draws on all US corporate patents with application dates from 1975 to 2007 that are granted by March 2013. The main finding of their regression analysis is that firms whose industries were exposed to a greater surge of Chinese import competition experienced a significant decline in their patent output. For instance, their results show that a one standard deviation increase in import penetration from China results in a 10 to 15 log-point decrease in patents.

The effects of import competition can be very heterogeneous among firms. Yamashita and Yamauchi (2020) considered the innovation responses of Japanese firms to Chinese import competition in the period 1995-2005. They find that patenting increased due to this competition, but the quality of innovation (measured as forward patent citations) fell. They note that their findings hold for firms that are globally active, but not for those that focus on the domestic market. Yang, Li and Lorenz (2021) consider import competition from China to Canadian firms during 1999-2005. They find that, on average, import competition stimulates product innovation, but it has a negative impact on process innovation. Aghion et al. (2021) study French manufacturers and their innovation in 2000-2007. They find that Chinese imports that are competing with the products of a firm hamper its innovation, whereas Chinese imports that might be used in its production process stimulate innovation.

2.2. Geography and innovation

The most recent line of research outlined in the previous paragraph focuses on the innovation impact of Chinese import exposure of US or Canadian domestic firms. It highlights the impact of import competition from "low-wage countries" on firms in developed countries. In addition, the distance-to-frontier approach has also shown an increase in studies, focusing on the heterogeneity effects of competition on innovation (Acemoglu et al., 2016). Theoretically, it draws upon specific elements of maximization whereby the innovation effects of competition vary according to some lower and upper bounds. Within this context, the distance-to-frontier approach emphasizes the argument that the impact of competition is conditional to a firm's distance to the technological frontier, be it a firm, sector or country. For instance, Aghion et al. (2005) find evidence that foreign competition of technological advanced countries encourages innovation to sectors close to the technological frontier but discourages innovation in laggard sectors. Bombardini et al. (2018) build upon this framework. They find evidence that only for firms above the 75% percentile of their respective productivity distributions, more import competition induced Chinese firms to patent more.

Further, Amiti and Khandelwal (2013) document significant quality differences among products imported by the US from countries of various income levels. Li and Zhou (2017) find that high-wage import competition led US firms to increase their innovation activities. But in contrast, import competition from low-wage countries did not always lead to more innovation activities. In addition, the effects are especially found in firms that are close to the technological frontier. In other words, there is a lot of heterogeneity.

Ding et al. (2016) use Chinese firm-level and international transaction data being linked to US industry data for the period 2000-2006. They provide support of a positive effect of import competition on R&D efforts (and TFP) in firms and industries that are close to the frontier due to a coping-with-competition effect. Further, the authors also distinguish the origin of imports according to countries' income level. They note that imports from high-wage countries embody higher sophisticated technology compared to imports from low-wage countries. This may lead to different type of innovative efforts depending on whether the firm is close or distant to the technology frontier. Only firms that are highly innovative may compete with foreign competition while the innovation incentives for laggard firms are diminishing. Indeed, the authors provide evidence that import competition originated from high-wage countries promotes innovation. Yet foreign competition from low-wage countries has no statistically significant effect.

2.3. Patents innovation strategies

As discussed above, import competition can be considered ambiguous for innovation. However, one further ambiguity may arise when one allows for diversification in firm innovation as a response to import competition. The valuation of patents, which refers to the value of the invention itself, is positively correlated with the technological importance of the invention. The technical valuation of patents corroborates with the idea that firms have innovation choices within their patent activities as a result of import competition. These innovation choices may induce incremental or radical innovation depending on the technological opportunity. The argument that patents are not only necessary for radical innovation can be reconciled with the work of Bryan and Lemus (2017). There it is theoretically shown that a reduction in trade barriers can force firms to shift to research projects that are less challenging but have the advantage to still maintain an industry-controlling patent.

First, it is reasonable to expect that not only the number of patent applications but also the “quality” of the patents can be explained by import competition. Forward citations can be used as a quality indicator of the value of the patent. According to Bloom et al. (2016), more intense import competition translates, at one hand, into an increase of the quality of innovation. This is due to a reallocation effect toward firms with high productivity levels that tend to be also more innovative. Mion and Zhu (2013) and Bloom et al. (2016) find that in response to greater import competition, firms (respectively located in Belgium and EU wide) upgrade their innovation quality. Bagayev et al. (2019) find that firms that are exposed to import competition increase their patent activities through international research collaboration. Their empirical results suggest that focusing on import competition picks up the effect from international research collaboration if the last variable is omitted. In a fuller model, on average the effect of import competition becomes negative, the effect of imported inputs is insignificant while the impact of the international diffusion variable is large and significant. The overall net effect of increased openness is positive. Zhao (2021) studies the effect of human capital input, R&D capital input and international competition on total factor productivity. He extends the Schumpeterian model of endogenous growth while incorporating special interdependence and uses data of 69 countries for 2000 to 2015. Just like Bagayev et al. (2019) he finds that there is an intricate interplay between the various explaining variables. And as in many studies, he finds heterogeneity: in this case, depending on the stage of development.

Second, another way of measuring the technical valuation of patents is to look at the extent to which innovation spans technological boundaries (Ahuja and Morris Lampert, 2001, Geerts et al., 2018). They draw on arguments from the literature on organizational learning and innovation management. It is postulated that firms that rely on backward patent citations that are more geographical diversified, may increase their technological importance. However, much depends on the extent to which firms are capable of creating synergies on a global scale (Geerts et al., 2018). For instance, Geerts et al. (2018) demonstrated in their study utilizing a panel of large R&D intensive European, US and Japanese firms, that firm reliance on more geographically dispersed “knowledge” results in better technological importance.

In similar lines, a third patent valuation dimension to be considered is that firms may also expand their so called “technological opportunities” through entering in new technological domains. This can be considered as a dynamic capability of maintaining a competitive advantage (Teece, 2007). It can be postulated that when technological opportunities are high, firm engage in more R&D because it will more likely to result in valuable inventions. Firms therefore are more likely to shift innovation projects towards opportunity-rich technology domains (Leten et al., 2016). Evidence by Zhang (2017) suggest that US firms were more likely to patent in new technology classes as a strategy to escape Chinese competition.

2.4. Size and innovation

It is also relevant to explore to what extent import competition has a heterogeneous impact on domestic innovation. The patent data statistics distinguishes patents related to national inventions that are filed at the Netherlands Patent Office (Octrooicentrum Nederland) and EPO (European Patent Office) patents. A national patent is different from an EPO patent; a national patent seeks protection solely on the national market. An EPO patent has a higher international dimension as it involves about 40 countries that are registered with the EPO. Patents can also be registered at both offices jointly. However, our patent data is constructed in such a way that it prevents this double counting of inventions. With this data option, an EPO versus national distinction is also suited to analyze the internationalization and the valuation of patent activities. Because it has also been shown that the most valuable patents are those that include filings in major international markets (Martinez, 2011; Statistics Netherlands, 2017). Firms that seek international patents protection and are internationally active, are willing to overcome these higher transaction costs if benefits exceed costs. Therefore, to undertake these costs, firms must undertake costly and risky innovative activities. This is more likely to be present among large firms as these firms are better equipped to cope with more intense competition than SMEs. SMEs are more likely to file patents only in the Netherlands. In comparison to EPO patents, the firm distribution of national patent data is more evenly spread throughout firm size distribution. We refer to Statistics Netherlands (2017) for a detailed firm-patent descriptive analysis.

2.5 Export response to more import competition

In order to cope with increased import competition, firms can also look at export opportunities so to increase new foreign markets. Because of larger markets, firms can achieve higher profits by innovating, resulting in a positive impact of exports on innovation referring to as the "market size effect" (e.g., Shu and Steinwender, 2019). Consistent with the market size effect, there is evidence that especially the most productive and technologically advanced firms are engaged in seeking increased access to export markets (e.g., Mayer et al., 2016; Aghion et al., 2018; Ahn et al., 2018). We note that a similar literature stream also looks at the so-called learning by exporting. However, the market size and the learning by exporting are conceptually different. In learning by exporting, a firm receives knowledge without necessarily investing in innovation- related activities. The market size effect by contrast would prompt a firm to intentionally increase innovation in order to reap the benefits of access to an enlarged market. (Shu and Steinwender, 2019). In line with the complementary effect between the market size effect and innovation, Coelli et al. (2022) find that access to larger markets via exporting leads to more innovation. Similarly, Guadalupe et al. (2012) who analyse the effect of foreign ownership on innovation find that innovation on foreign acquisition is associated with access to exports via the parent firm. In similar lines, Coucke and Sleuwaegen (2008) observe that import competition from low-wage countries has led firms to increase their offshoring activities to low costs destinations thereby increasing their survival rate. And Castellani and Fassio (2019) show that importing new inputs led to Swedish firms exporting new products. They note that import offers access to new technologies and better combination of inputs, and that firms can benefit from this since it can lead to better or improved export products.

2.6 Research questions

Based on the literature review, the overall effect of import competition on innovation remains ambiguous. Theoretically, there is no clear consensus that can be made on the expected impact of trade exposure on innovation. While there is an analysis framework for the impact of import competition on the local firms' innovation activities, many studies showed a clear impact following the ambiguity that can be found from theory. In particular, these studies lay out different angles that can be in addition considered as important factors along with the import competition, which we have highlighted in this literature review.

To clear this ambiguity and contribute to the ongoing debate on the role of import competition on innovation, this paper proposes and addresses the following research questions:

RQ1: What is the impact of import competition on the number of patents at the firm-level?
RQ2: Does import competition lead to better and more qualitative patents?
RQ3: Does the origin of import competition matter for its impact on the different innovation strategies?
RQ4: Do SMEs react differently to import competition (and its origin) than large enterprises?

Whereas the first research question has often been the object of study, the other three are new and form our contribution to the literature.

3. Data construction

Our data consists of an unbalanced panel of over 2400 firms situated in the Netherlands, during the period 2000-2010. It is the population of firms that have applied for at least one patent during the years 2000-2010. We end the sample data in 2010 because of data limitations. At Statistics Netherlands, efforts to extend the database to more current years is in progress during the time of this study. The Netherlands Patent Office (Octrooicentrum Nederland) and Statistics Netherlands matched the entire population of patents applied for by entities in the Netherlands at the European Patent Office and/or the Netherlands Patent Office to entities in the Dutch General Business Register. These are subsequently aggregated to the Dutch enterprise group. In a second step, we match trade data to Dutch manufacturing industries in order to create measures of changing import competition. The final dataset can be used, under strict conditions, in the remote access environment of Statistics Netherlands.

3.1. Patents and firm-level data

As described in the literature review, we look at several innovation outcomes. These are the number of patent applications, the number of forward citations, patenting in new technology classes and the geographic scope of backward citations. We now describe how the measures are constructed.

To collect the firms that applied for at least one patent, we used the database of the total population of patents applied for in Europe (at the European Patent Office (EPO)) or in the Netherlands (at the Netherlands Patent Office). The database can be made accessible to external researchers through remote access. This patent data gives us information such as the application number, the patent owner (name of the firm), patent title, technology field, name of the inventor, publication year and location. However, firms may register patents under different names, for example the name of a local plant, whereas we are interested in the patents of the whole enterprise group. To match firm-owned patents to enterprise group data, we use the General Business Register data, issued yearly by Statistics Netherlands. It contains information on a firm's ownership structure, such as names and direct ownership of all their subsidiaries and owners. For each firm with a patent we pinpoint the Dutch enterprise group (not necessarily the ultimate parent) corresponding to the firm (enterprise). We refer to Vancauteren et al. (2017) for a more detailed description of the data. That paper applies a firm-level analysis using EPO patents for the period 2000-2006. For the purpose of the current paper, we extended the database to the most recent year 2010 that can be retrieved from the PATSTAT database within Statistics Netherlands. In addition, we also incorporate Dutch patents in this paper.

We also include information about forward citations. A forward citation means that a patent is cited by a later patent, which captures the relationship between a patent and subsequent technological development that build upon it. The number of forward citations of a firm's patents is informative about the intrinsic quality of patents (Harhoff et al., 1999). We use so-called patent family data to construct the number of citations. A patent family refers to the set of patent applications across countries that protect the same technological invention. This is defined as being exactly the same priority or combination of priorities. For this reason, family patent data prevent double counting. The purpose of using family patent data as an indicator of patent value is to characterize the extent to which firms are involved with the internationalization of technology. Firms that seek international patent protection do so for the most valuable patents (Martinez, 2011). We use the so-called DOCDB families, which include EPO expert control and consider the number of forward citations by later patents that belong to the same patent family. The forward citation data is restricted to all patents granted up to the year 2010 with forward citations until autumn 2016. See Martinez (2011) for an overview on the various definitions that are applied using the PATSTAT patent citation database.

The firms are then matched to firms that report R&D. We extract R&D data from the Community Innovation Surveys (CIS) and R&D surveys that are collected by Statistics Netherlands. In the CIS and the R&D surveys only a subset of innovating firms are also R&D performers. This means that firms with missing R&D expenditures who are still engaged with some form of innovation activity are not accounted for. In this analysis, we do not consider sample selection bias in the R&D variable. We refer to Vancauteren et al. (2017) for a detailed analysis where missing R&D expenditures are also analysed, to bypass selectivity bias, using panel data techniques. The R&D surveys report R&D expenditure in the odd years while each of the CIS surveys measures R&D expenditure in the even years of our sample period 2000-2010. The data on the number of employees, ownership structure, the number of subsidiaries (the number of enterprises that make up an enterprise group that are bound together by legal and/or financial links and controlled by the group head) and the number of different industries/activities of all enterprises within the enterprise group is taken from the general business register. The exact manufacturing industry category assignment scheme that we use throughout this paper, based on ISIC Rev. 4 codes, is industry codes 10-31.

We now turn to the description of the two additional innovation outcomes: patenting in new technology classes and the geographic scope of backward citations. The EPO classifies patents in at least one eight-digit technology field based on the International Patent Classification (IPC) system. Technology fields are aggregated into 628 broader four-digit IPC classes that we use in our paper. In line with prior work (e.g., Ahuja and Lampert, 2001; Leten et al., 2016) a technology field is defined as new-to-the-firm if the firm was not active (did not patent) in the technology field in the previous four years. For the geographic scope, we follow Geerts et al. (2018) and calculate the inverse of the Herfindahl index for the geographic scope of each patent j of firm i in year t. Then we aggregate at the firm level by taking the average of all patents of firm i in year t. Geographic scope is defined as the spread of backward citations of patent j of firm i across countries.

In the robustness tests, we use two measures of internationalization: yes/no variables for exports (of goods) and receiving foreign income from foreign capital. Both measures indicate the situation at enterprise group level. The export data follows from matching the trade in goods data with the business register. It is available for the whole period 2000-2010. The foreign income variable is obtained from survey and fiscal data. It is available for the period 2005-2010 only.

3.2. Import competition data

We use two main data sources to construct the measure to capture import competition. Namely, the Dutch international trade in goods statistics (at product x country level) and statistics from National Accounts about trade and turnover (at product by industry level). Now we explain how the measure of import competition was constructed.

Estimating direct import competition

In order to measure import competition, we follow Chakravorty al. (2017). They set

$$Import\ competition\ from\ China\ in\ industry\ j\ in\ year\ t$$

$$= \frac{M_{j,t}^{China}}{Y_{j,t} + M_{j,t} - X_{j,t}}$$

Here $M_{j,t}^{China}$ are the imports from China of products of industry j, $Y_{j,t}$ is the production of industry j, $M_{j,t}$ the total imports of products of industry j and $X_{j,t}$ the exports of products of industry j. This is all at time t.

Contrary to Chakravorty et al. (2017) we will mainly use data from the National Accounts Statistics. We do not use turnover from Structural Business Statistics. We use trade statistics only to create the import country distribution at product level. This is for the following reasons:

- About half of Dutch trade in goods considers of re-exports (Statistics Netherlands, 2016), which is no competition for sales on the domestic market. The trade statistics do not yet contain imports for re-exports; national accounts statistics do.
- National accounts integrate the data from all different statistics and make it consistent.
- During the period under concern, 2000-2010, both the turnover statistics and trade statistics changed concepts, definitions and methods. Only national accounts repaired the time series.

We arrive at the numbers $Y_{j,t}$, $M_{j,t}$, $X_{j,t}$ and $M_{j,t}^{China}$ in the following way.

- We distinguish 20 manufacturing industries in total, shown in Table A1, the production value for 81 different industrial goods and the industry where they were produced. We use constant prices with base year 2010. The source is a database of national accounts.
- Y_j, total production of industry j, is extracted from the same database of national accounts.
- This database also contains, by commodity, the value of imports excluding imports for re-exports and exports excluding re-exports. Aggregating the value of imports and exports of commodities that were assigned to an industry j yields the values of M_j and X_j.
- We match the commodity codes from the trade statistics to those of national accounts. Scale, on product level, the value of imports (and exports) from the trade statistics to the

value M_j of national accounts. At product level, imports from China are scaled with the same factor. Aggregating the products by industry yields the number $M_{j,t}^{China}$.

To estimate import competition for an enterprise group, we take its composition into account. Its underlying enterprises might be active in different industries than the enterprise group itself. First, we calculate the import competition for each of the industries of the underlying enterprises. Then we weigh these results on industry level using employment at each enterprise as a weight to arrive at import competition for the whole enterprise group.

We also include domestic competitive pressure in our analysis since this might affect a firm's patenting behavior as well. We follow Martin et al. (2011) and measure the level of domestic competition using a Herfindahl index of industrial concentration being the sum of the quadratic relative firm-sizes,

$$H_{k_i t} = \sum_{j \in S_{k_i t}} \left(\frac{employees_{jt}}{employees_{k_i t}} \right)^2,$$

where k_i denotes the industry to which firm i belongs and $S_{k_i t}$ is the set of firms belonging to industry k_i at time t. The variable "competition" defined as $\frac{1}{H_{k_i t}}$ measures the degree of domestic competition for firm i in industry k_i faces at time t. The inclusion of these variables is motivated by previous patent studies (see, for example, Vancauteren et al., 2017).

3.3. Data description

Figure 1 shows competing imports and the total number of Dutch patent applications to the EPO in the manufacturing sector in each year. The series shows that the number of patent applications is modestly declining over time, whereas the total import of competing manufactured goods (in constant prices, thus corrected for price changes) seems to be following a different trend. During the 2000-2010 period, the total number of patent applications (right axis) in the manufacturing sector has declined from 3390 to 2950 which amounts to a decline of 13 percent. Whereas the exposure of Dutch manufacturing to import competition rose from 91 to 97 billion euros (left axis, constant prices), an increase of 7 percent during the same period. We observe a similar trend when we consider the import competition from countries outside the EU. The import competition from these countries increased by 6 billion euros which amounts to an increase of 17 percent.

Before we discuss the regression results, summary statistics of our key variables (in the transformation used in the analysis) are shown in Table 1. The statistics are based on the total sample of firms from the period 2000-2010. The overall sample consists of 2313 panel firm-year observations. The number of firms is 1472. The unweighted average firm in our sample applies approximately for 7.8 patents a year, with an average forward citation count of 1.05, an average of 1.845 new entry patents and the geographical scope is equal to 1.695. A firm spends on average exp (6.296) = 542 thousand euros on R&D. On average the annual import competition is equal to 0.416 (41.6%), 40% of the panel firms have a foreign parent, firms are on average involved in 3.2 industries and consist of 5.2 enterprises. The average annual domestic competition is exp (0.334) = 1.396, corresponding to a Herfindahl index of 1/0.873. The distribution of the patent variables is quite skewed, while most of the other variables are more evenly spread. Table 2 provides similar summary statistics, now by industry.

4. Empirical implementation

We estimate a similar model as the one used in Autor et al. (2013). The discreteness of patent data motivates the use of count panel data techniques. An important characteristic of our data is skewness. We find for many firms zero patent counts during some of the years. The zero-citation patent counts also occur for firms that applied for a patent (whether granted or not) and received no forward citations. We observe that 60% of our sample includes panel-year firms with zero patent applications. Similarly, Bound et al. (1984) observe for the US that zero patent firms represent 60% of their sample; Crépon and Duguet (2007), using French data, find that these firms represent 73% of their sample.

The zero-patent count is year-firm specific and occurs when a patent firm has not applied for a patent. A firm can decide not to apply for a patent for many reasons. E.g., difficulties in R&D process, technological and market uncertainty or one-time technological activities. To take this excess of zeroes into account, we use a pooled hurdle model allowing for unobserved heterogeneity. Our model with reference to the innovation stage draws heavily from Vancauteren et al. (2017). The authors use a static random effects hurdle model controlling for zero inflation. As a robustness check, they also estimate a zero-inflated model.[1]

[1] We also ran a sensitivity test by considering a zero-inflation model. The results are consistent with those shown in the subsequent results. The choice of a Hurdle and two-part model is supported by the data. Technical details and sensitivity results are available upon request. We thank the referee for pointing out this robust analysis using count data.

Let a firm be indicated by the sub index i, industry be indicated by the sub index j and time by the sub index t. We first introduce

$$P(y, \lambda_{it}) \equiv \frac{\exp(-\lambda_{it})\lambda_{it}^{y}}{y!}, y \in \{0, 1, 2, \dots\} \quad (1)$$

where λ_{it} is the Poisson distribution parameter. Let $PAT_{it} = y$ be the number of patents. We model $ln\,\lambda_{it}$ as

$$ln\lambda_{it} = \alpha_{1i} + \delta_1 IC_{i,t-1} + \boldsymbol{\beta}_1' \boldsymbol{X}_{\boldsymbol{1it}}, \quad (2)$$

where IC_{it} is the level of import exposure for industry j to which firm i belongs; we allow for a time lag as patent activities and import competition may not coincide contemporaneous. The vector of independent variables $\boldsymbol{X}_{\boldsymbol{it}}$ represents firm i characteristics. Turning to the coefficients, α_{1i} is a time-invariant unobserved firm-effect, and δ_1, β_1 include the unknown parameters. The time-invariant unobserved firm-effects α_{1i} are assumed to be standard normally distributed (conditionally on $IC_{i,t-1}$ and $\boldsymbol{X}_{\boldsymbol{1it}}$). Following Wooldridge (2005), we model the unobserved heterogeneity as being dependent on the average of the continuously distributed explanatory variables with additional random effects that are uncorrelated with the regressors.
In addition, the model may need to be adapted to a corresponding with-zeros model in case of excess zeroes, meaning more zero counts in the data than predicted by a Poisson model. Then, the hurdle or two-part model is a commonly used count model taking the excess of zeros into account. We specify the panel version of the hurdle model as follows,

$$\Pr(PAT_{it} = 0) = (1 - p_{it})P(0, \lambda_{it}), \Pr(PAT_{it} = y) = p_{it}P(y, \lambda_{it}), y \geq 1 \quad (3)$$

where p_{it} represents the probability that firm i did pass a threshold with positive counts. Thus, conditional on the event that the threshold is crossed, the distribution of positive patents outcomes follows the Poisson distribution, see Cameron and Trivedi (2013). In a hurdle model, the decision to patent is usually made on the basis of a first invention and the decision to apply for additional patentable inventions is based on the outcomes of this first decision. Therefore, we might expect different decision criteria concerning the first patent and additional patents.
We model the probability p_{it} as

$$logit\ p_{it} = \alpha_{2i} + \delta_2 IC_{i,t-1} + \boldsymbol{\beta}_2' \boldsymbol{X}_{\boldsymbol{2it}}, \tag{4}$$

where α_{2i} is the unobserved firm-effect (which we define similarly like α_{1i} using the Wooldridge approach), $\boldsymbol{X}_{2it}$ is the vector of the same independent variables as in $\boldsymbol{X}_{1t}$ and $\delta_2, \boldsymbol{\beta}_2$ include the unknown parameters.

To fit the pooled hurdle models with random effects, we adopt the approach from Min and Agresti (2005) where we allow for possible correlation between the unobserved heterogeneity. The Poisson model (2) assumes equality of the mean and the variance in the distribution of the dependent variable. As this property may need to be properly handled according to the data, we will also consider a negative binomial distribution in (1). For a detailed discussion on the zero-dominance in count models, we refer to Cameron and Trivedi (2013).

To explain patent activities we include in the vector $\boldsymbol{X}_{\boldsymbol{1it}} = \boldsymbol{X}_{\boldsymbol{2it}}$ the following independent variables: R&D measured as the lagged log of (1 + R&D expenditures per employee), employment measured as the log of number of employees in full time equivalents ("Log Employment"), a variable indicating the number of domestic firms in the enterprise group under concern ("number of firms"), a dummy variable indicating whether a firm is under foreign control of domestically owned ("Foreign Y/N 1/0"), a variable indicating the number of industries of enterprises within the enterprise group ("number of activities"), and domestic competitive pressure ("competition"). The number of activities for each firm (enterprise group) i in year t are the number of different 3-digit ISIC Rev. 4 codes that correspond to all the enterprises in the enterprise group. The domestic competition variable has been explained earlier.

5. Empirical results

We now consider the estimates of the patent equation discussed in section 4. Table 3 presents the baseline results. First, a likelihood ratio test comparing the Poisson model with the Negative Binomial model reveals that in all cases the Negative Binomial is to be preferred. As shown (row with "alpha"), the hypothesis that the overdispersion parameter equals zero (i.e., H_0: alpha=0), is conclusively rejected. Therefore, we only report the outcomes based on the Negative Binomial distribution. Six variants have been estimated and we will discuss them in more detail in section 5.1 and section 5.2. In Model 1 we report, using the hurdle model, the Maximum Likelihood based results of the number of patent applications, with random effects, including the lagged value of import competition, the lagged value of the log of (1 + R&D

expenditure per employee) and the log of employment. In Model 2 we present the same model including the entire unobserved heterogeneity but using the full model. In model 3, we consider the total number of forward citations as a dependent variable as a proxy for patent quality. In model 4, 5 and 6, we consider respectively domestic patents, geographic scope of backward citations and patenting in new technology classes as alternative measures of the dependent variable.

5.1. Patents and import competition

We find that the parameter estimates for import competition are statistically significant and positive for both the propensity patent part of the model and the patent count part. This indicates that the propensity to patent and the number of patents is increasing with increasing import competition. The coefficient of 1.057 in model 1 at "Logit(Y/N)" indicates that an increase in import competition by one percentage point is estimated to increase the patent propensity by 1.057 percentage points. The coefficient of 1.115 in the column next to it, at "Patents", indicates that a one percentage point increase in import competition leads to a firm applying for 1.115 patents more. We note that including more control variables, as in model 2, affects little the estimation results. The import competition effect remains robust across specifications. The coefficients of the log of employment are always positive, indicating that the propensity to patent and the number of patents is increasing with firm size. In addition, more R&D per employee is positively related to the propensity to apply for a patent and to the number of patents. Different activities in the same enterprise group only affects its propensity. The number of enterprises in the enterprise group and foreign ownership however, are negatively related. Domestic competition seems to play a negative impact (yet not statistically significant) on patenting. This suggests that as domestic competition increases, firms are less engaged with their patent applications.

5.2. Patent quality, new technologies and internationalization

In model 3 of Table 3, we adopt the same specification as in model 2, where the dependent variable is measured by the total number of forward citations per patent. Our results reveal that when patent citations are used as an indicator for the technological importance of the patent, the coefficient on the effect of import competition retains its significance and magnitude. In other words, on average import competition does also to lead to "better" patents. We also find that the propensity to have a cited patent is also increasing with more intense import competition. What also has a positive impact on the quality of patents, are the expenditures on R&D and the number of activities within an enterprise group. However, there is also some evidence that the larger the enterprise group in terms of the number of controlled subsidiaries, the lower the number of citations of its patents. This indicates that these patents are on average of lower quality. It does not imply that larger enterprise groups have innovation of lower quality. Other factors, such as strategic behavior to abstain from applying for a patent to prevent competing enterprises from gaining knowledge, may play a part.

Model 4 will be discussed in 5.4. In model 5 we use the alternative measure where we consider the technical valuation of patents by looking at its international dimension. We express the dependent variable into its geographic scope across countries. As found in model 3, the positive import competition variable is still confirmed and significant. Note that in comparison with model 2 and 3, the coefficients of the other variables are little affected. In the final columns, in model 6, we have defined the dependent variable as the variable that looks at technical opportunities in terms of shifting towards the entry of new technology classes. When doing so, we find that the coefficient on import competition is no longer significant for explaining the number of new entries. However, import competition is positively related to the propensity to enter into new technology classes. This suggests that import competition does drive firms to seek new opportunities such as new technologies, enlarging the extensive margin, while it does not have any effect on the actual quantity of new novel innovation.

5.3. Import competition by destination

As mentioned previously, it is also relevant to find out if there are any heterogeneous effects of import competition on innovation depending on the country (group) or origin of import. Therefore, we estimate the same models as in Table 3, but with import competition from different regions. First, we consider three import source destjnations: EU countries, China and the Rest of the World (RoW). The EU destination considers the group of countries that joined the EU before 2010. The results in Table 4 indicate an overall positive impact of import competition on both the number and knowledge value of patents according to each of the models that we described in the previous subsection. The overall results reveal that especially import competition from the RoW seems to lead firms to adopt better and more diverse patents both in terms of patent propensities and volumes. Both import competition from the EU and China lead rather to larger propensities of applying for patents as well as new IPC entries.

We also carried out the analysis for import destination country groups according to low-wage, middle and high-wage countries as by the World Bank. The results reveal that only the coefficients of import competition originated from high-wage countries are positive and significant.

Overall, our findings are in line with the existing literature: the origins of imports also matter. The key message from these results is that import competition from high-wage countries, which are usually characterized by more advanced technology, lead firms to engage in more innovative efforts. According to Ding et al. (2016), more important competition from advanced countries induce firms to seek higher quality and higher technology intermediates so to increase their competitiveness.

5.4. Dutch versus EPO oriented patenting activities

We now consider applications for national patents. The corresponding firms are, compared to the firms applying for EPO patents, more often SMEs. Hence, these results will yield information about the reaction of SMEs to import competition. The results summarizing the impact of import competition on the number of domestic patent applications are listed as model 4 in both Table 3 and 4.

The nature of the results about domestic patent applications is comparable to that of those about the patents applied at the European Patent Office. Namely, import competition is related to larger propensities to apply for domestic patents and the number of domestic patents. For example, an increase of 1 percentage point in import competition for a given enterprise group will on average lead to an increase in Dutch patent applications of 1.3. When looking at destinations, we that import competition from China, EU countries, high-wage countries and middle-wage countries result in higher domestic patent activities.

5.5. Internationalization response to more import competition

We now extend the models by taking into account that a firm might react to import competition by internationalization. See the literature review for more details. In Table 5, Variant I, we present out results. They are the same models as before, but we added an extra control variable at firm level that captures the foreign income from foreign capital realized from all firms within the enterprise group. This data is only available from 2005 onwards as it makes a distinction between the income realized from foreign affiliates and domestic affiliates. We measure the foreign income variable as a (Yes/No, 1/0) categorical variable. As can be seen, we find positive and significant coefficients that are the same in magnitude as what we found in the baseline results from Table 3.

In Table 5, Variant II, we instead include an export dummy at the level of firm as an extra control. This data is available for the entire sample. However, due to the fact that the Business Register underwent major changes in 2006, 2009 and 2010 that affected both the sector classification as well as the firm-enterprise group identification, this is not an efficient approach to include in the baseline estimation. However, it can give a good initial idea of the effect of import competition on innovation. As can be seen, the pattern of the coefficients is largely the same and we still find a significant effect of import competition on both the quantity and quality in patenting activities.

6. Further robustness checks

Finally, we discuss possible alternative explanations that potentially might be driving our findings and results. We consider the lag structure and the potential bias that might arise for estimation under the exogeneity assumption.

6.1. Instruments

An alternative explanation for finding a positive impact of import competition on patents may be that this result is driven by unobserved time-varying factors that affect both the firm's innovation performance and import competition. For example, firms that want to increase their innovation performance will make various innovation investments and focus on new product developments. These investments might jointly be determining innovation performance and import competition. This type of unobserved firm-level time-varying heterogeneity is not accounted for in our main estimations (which do include a control for time-constant firm effects). Therefore, we ran a GMM regression for our main regression where we instrument the import competition variable.

We use the Poisson estimator derived by Blundell et al. (2002) which accounts for both fixed effects and lagged dependent variables. In particular, we instrument the import competition variable using the yearly percentage change in non-Dutch exports to the rest of the world except the Netherlands. Following the literature (Autor et al., 2020; Hummels et al., 2014; Bloom et al., 2016), the idea of this instrument is that the growth in import competition across other countries may be the result of exogenous shocks (e.g., productivity growth, know-how, macroeconomic policy shocks) reflecting changes in the export capacity. The additional instruments we use are average shares of lagged employment and the year dummies. As further support for the validity of the instruments, we note that additional testing shows that our GMM and the instruments pass the restriction (using the Sargan test).

The GMM results are reported in Table 5, Variant III and almost similar to the baseline estimations: the coefficient of import competition is insignificant when explaining citations but significant for both count and geographical scope as well as for the entry of new patents.

6.2. Alternative lags

A final approach to alleviate potential endogeneity problems and to consider the robustness of our results, is to use lagged values of the explanatory variables. Up to this point, we only have included the t-1 variable of the R&D and import competition variable whereby the other controls are expressed in year t. In Variant IV of Table 5, we express the controls in t-1 lags and include the t-2 lags of both the R&D and import competition variables. Overall, the results in terms of the effect of import competition on patents, using longer lags, are only a little affected. That is, the effects of import competition retain their sign and their significance. Except that we find a significant effect on the level patent counts, the positive effect of import competition on both the probability and the level of patenting remains confirmed.

7. Discussion and concluding remarks

The main research questions at the start of the article were whether import competition has an effect on Dutch innovation and whether it has an effect on the quality of innovation. The literature has found mixed evidence, depending on the country or region under concern. Sometimes import competition would slow down innovation, sometimes the extra competition would stimulate it. And sometimes the quality of innovation would be higher.

Following and being consistent with the analysis framework on measuring import competition, the only change is that we measure various firm-level innovative measures using patent data. The way we measure innovation is based on three concepts:(i) firm level counts of number of patent applications and the quality of those patent applications by the numbers of citations, (ii) geographical scope of knowledge diffusion and (iii) the entry of new patents. Our findings are mainly in the following aspects: import competition has a positive impact on the number of patents (RQ1), on the quality of patents (RQ2), the origin of import competition matters (RQ3) and results are similar for SMEs and large enterprises (RQ4). We will now discuss our findings in more detail.

First, we show that higher import competition in the Netherlands has a positive impact on both the probability that a firm applies for a European patent and the number of patent applications as well (RQ1). And it has also influenced the quality of the patents; with more import competition the number of citations, geographical scope of knowledge and new technology does also increase significantly. These results unmask a striking homogenous response across firms of different innovation activities suggesting that more quality-driven innovative firms put them in a better position to reap the benefits of more import competition. These results can be reconciled with the model of Aghion et al. (2005) where greater competition discourages laggard innovating firms to engage in innovation as they become more distant from the frontier. Our results contradict the findings of Autor et al. (2020) that U.S. firms respond negatively to import competition in their patent output. On the contrary, in the Dutch case import competition may cause the overall economic efficiency to increase and the gain of high-skilled employment opportunities as a result of higher innovative activities.

Second, our findings about the positive link between import competition and quality of innovation (RQ2) are in line with the literature. Mion and Zhu (2013), Bloom et al. (2016) and Bagayev et al. (2019) have similar results, for firms in Belgium and the EU, respectively. See the literature section for more details.

Third, whereas most studies only consider import competition from China and other emerging markets, we also take high-wage countries into concern (RQ3). We find that import competition from EU member countries has only a positive impact on the probability to engage in patent counts and quality (RQ2), whereas there is no statistically significant influence on the count variables. The literature mostly focusses on import competition from emerging markets, usually low-wage or middle-wage countries, and as we have seen in the literature section, this often has negative impact on innovation although there is substantial heterogeneity in the results. It is less common to consider import competition from high-wage countries, such as the members of the European Union, even though the great majority of trade takes place with those countries. Exceptions are Li and Zhou (2017) who found that import competition from high-wage countries spurred innovation in the US, and Aghion et al. (2005) who find that competition from technological advanced countries works out positively on sectors close to the technological frontier yet negatively on other sectors. However, it is possible that their exports are of higher quality (compare Amiti and Khandelwal, 2013), and in that sense are closer to the production of Dutch manufacturers and therefore are more competing. Our results confirm that more import competition from advanced countries induce firms to seek higher quality in terms of patenting so to increase their competitiveness.

Fourth, due to our unique datasets, we can also take effects of import competition on innovation by SMEs into account. We are not aware of any other examples in the literature. We do not only have a dataset with patent applications at the European level, where it is mainly large enterprises who apply, but also a dataset with applications for patents valid in the Netherlands only. SMEs are far more likely to apply for a patent that is valid in the Netherlands only and not at the European level. We find that SMEs, just as large enterprises (RQ4), have a larger propensity to apply for and to obtain domestic patents when import competition is higher.

Our findings also sparked some other thoughts. First, it might come as a surprise that the rise of imports from China does not have a compelling effect on Dutch innovation. However, Suyker et al. (2006) note that in 2000 China is competing on different markets than the Dutch producers. They note that "the products China exports intensively are not very important for Dutch producers. This holds both for goods intensive in low-skilled labor (textile, shoes, toys, etc.) and for consumer electronics assembled in China". They conclude that "Chinese and Dutch exports are more complements than substitutes". Although imports from China had a metamorphosis, "From t-shirts to tablet PCs" (Lemmers and De Wit, 2012), it is possible that this conclusion still holds for the period 2000-2010 that we study in this paper.

Second, MNEs are linked to import competition. Bilir and Morales (2020) point out that a multinational might transfer technological improvements to all its subsidiaries. In other words, the positive impact of imported foreign products on innovation is likely to be partly caused by the transfer of knowledge of Dutch multinationals to its foreign subsidiaries who then export to the Netherlands. These exports, Dutch imports, also include non-competing goods that are unlikely to impact innovation in a negative way.

Third, it is unclear whether the results would also hold for a more recent time frame; the results might be outdated. One reason was already mentioned above; the type of products imported from China changed through time. Furthermore, the share of imports from China rose from 3 percent in 2000 to 9 percent in 2010 and 11 percent in 2020. Although our analysis accounts for the size of import competition, it is possible that there exists a threshold after which import competition has a stronger effect on innovation. Lastly, the world keeps changing and anything that holds for 2000-2010 might not hold in 2022 anymore. Even results for the EU might be different for a more recent period.

There are several promising future research directions in order to understand innovation and its driving factors. From a theoretical point of view, one should probably pay more attention to the roles of foreign direct investment and offshoring and not simply focus on import competition. Regarding the latter, especially offshoring in addition to import competition, has potentially a number of positive implications for innovation (and highly skilled workers). More research is needed to comprehensively assess the impacts of import competition and offshoring on the innovative activities of the firm (especially considering that some firms will actually boom because they are competitive from an international perspective) and it would be an interesting avenue to further explore. In this context, an interesting question is what is the key driver of the positive impact on innovation: import competition or outsourcing (when appropriately measured)?

Other directions of future research would be the use of big data, possibly in connection with the skill set of employees of innovating firms. For example, Tunc-Abubakar et al. (2022) note that big data usage can positively impact innovation. However, they show that diagnostic capability, the capacity of the firm to extract quality insights from big data, is essential. Of course, this capacity is closely related to the skills of the employees of the firms. Hayajneh et al. (2022) link business analytics and π-shaped skills (a combination of soft skills and two or more hard skills) to innovation. Elayan et al. (2022) in turn show that knowledge-based HR practices lead to increased π-shaped skills and that this in turn (confirming Hayajneh et al.) results in more innovation. Elayan et al. note that the majority of research on knowledge-based HR practices is on SMEs. We think that it deserves attention to extend it on multinationals as well, disentangling different effects in multinationals on innovation, such as being active in different countries, having different HR practices and having different employees.

Practical implications of the findings are that the fear for import competition on innovation in the Netherlands seems unfounded. That is both for large enterprises and SMEs. Imports from high-wage countries even stimulate innovation. And the perceived danger from competition from China on innovation is not confirmed in the analysis. Therefore, trade policies that hamper imports in order to protect national innovation seem unfounded. On the contrary, for innovation it would be good to stimulate import competition. Note that our analysis did not study other relevant effects of import completion. In general, it would be worthwhile for practice and policy to quantify the possible discrepancy between feared outcome and actual outcome of import competition in many dimensions. The data compiled for this article could be used to answer questions in many different settings. For example, to study the relation of import competition with employment (which people and what do they do), working conditions (more pressure, more overtime and more stress or not at all), crowding out of local enterprises, regional effects and wages. Smits et al. (2018) already used a variant of this data and found that rising import competition is connected to a rising relative demand of non-routine skills. Although there is a vast collection of literature on the effects of import competition, this literature and this article note that effects of important competition can be very heterogeneous. They may vary by country, country of import, industry and type of firm. Therefore, policies are ideally based on analysis that is as specific as possible.

Our results have also an impact on the literature that uses Helix models of innovation which look at the relationships among government, business enterprises, entrepreneurship, change and socio-economic developments (Campbell and Carayannis, 2014; Carayannis and Campbell, 2009, 2010). For example, though the findings of our study show that import competition encourages firms to innovate more and better, there are also hidden costs. For instance, the work of Colantone et al. (2019) show that import competition is found to substantially raise mental distress, through worsened labour market conditions and increased stress on the job. These findings provide evidence of an important hidden cost of globalisation which may be of great importance for stakeholders from government, industry and academics. As a result, so called quadruple (and quintiple) Helix models of innovation within the context of globalisation, as proposed by Carayannis et al. (2020), provide interesting insights for decision-makers to think about policy formulation in this particular context.

References

Aghion, P., Bloom, N., Blundell, R., Griffith, R. & Howitt, P. (2005). Competition and innovation: an inverted U relationship. *Quarterly Journal of Economics*, *120*, 701-728.

Aghion, P., Bergeaud, A., Lequien, M. & Melitz, M. (2018). The Impact of Exports on Innovation: Theory and Evidence. *NBER Working Paper* no. 24600. Cambridge, MA.

Aghion, P., Bergeaud, A., Lequien, M., Melitz, M. & Zuber, T. (2021). Opposing firm-level responses to the China shock : horizontal competition versus vertical relationships ? Retrieved February 18, 2022, from https://scholar.harvard.edu/files/aghion/files/opposing_firm-level_responses_to_the_china_shock_jul2021.pdf.

Ahn, J., Han, H. & Huang, Y. (2018). Trade with Benefits: New Insights on Competition and Innovation. *IHEID Working Paper* no. 07-2018, Economics Section, Graduate Institute of International Studies, Geneva, Switzerland. Retrieved February 18, 2022, from http://repec.graduateinstitute.ch/pdfs/Working_papers/HEIDWP07-2018.pdf

Acemoglu, D, Autor, D., Dorn, G., Hanson, G. & Price, B. (2016). Import competition and the great US employment sag of the 2000s. *Journal of Labor Economics 34*(S1), S141-S198.

Akcigit, U., & Melitz, M. (2021). International Trade and Innovation. *NBER Working Paper* No. 29611.

Ahuja, G., & Morris Lampert, C. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic management journal*, *22*(6-7), 521-543.

Amiti, M. & Khandelwal, A. (2013). Import competition and quality upgrading. *Review of Economics and Statistics*, *92*, 476-490.

Arora, A., Belezon, S. & Patacconi, A. (2015). Killing the golden goose? The decline of science in corporate R&D. NBER Working Paper No. 20902.

Autor, D., Dorn, D. & Hanson, G. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economics Review*, *103*, 2121-2168.

Autor, D., Dorn, D., Hanson, G., Pisano, G. & Shu, P. (2020). Foreign competition and domestic innovation: Evidence from US patents. *American Economic Review: Insights, 2*(3), 357-374.

Bagayev, I., Davies, R. & Kogler, D. (2019). *Innovation and technological content of imports.* Final report, European Patent Office, Academic Research Programme. Retrieved February 18, 2022, from https://documents.epo.org/projects/babylon/eponet.nsf/0/A69432F980D71284C12584F5003DE05C/$File/ARP_report_Bagayev_en.pdf.

Belderbos, R., & Somers, D. (2015). Do technology leaders deter inward R&D investments? Evidence from regional R&D location decisions in Europe. *Regional Studies, 49*(11), 1805-1821.

Bilir, L. K., & Morales, E. (2020). Innovation in the global firm. *Journal of Political Economy*, *128*(4),1566–1625.

Bloom, N., Romer, P. & Van Reenen, J. (2013). A trapped-factors model of innovation. *American Economic Review, 103*, 208-213.

Bloom, N., Draca, M. & Van Reenen, J. (2016). Trade-induced technical change? The impact of Chinese imports on innovation, IT, and productivity. *The Review of Economic Studies, 83*, 87–117.

Bloom, N., Romer, P., Terry, S. J., & Van Reenen, J. (2021). Trapped factors and China's impact on global growth. *The Economic Journal, 131*(633), 156-191.

Blundell, R., Griffith, R., & Windmeijer, F. (2002). Individual Effects and Dynamics in CountData Models. *Journal of Econometrics, 108*(1), 113–131.

Bombardini, M., Li, B. & Wang, R. (2018). Import competition and innovation: Evidence from China. Retrieved February 18, 2022, from https://drive.google.com/file/d/1nYqghqOgaKIksIsD4EdSCZBFSLi3P0VL/view.

Bound, J., Cummins, C., Grilliches, Z., Hall, B. & Jaffe, A. (1984). Who Does R&D and Who Does Patents? in Z. Grilliches (ed.), *R&D, Patents and Productivity*. University of Chicago, Press for the National Bureau of Economic Research, Chicago.

Bryan, K., & Lemus, J. (2017). The direction of innovation. *Journal of Economic Theory*, *172*, 247-272.

Cameron, C. & Trivedi, P. (2013). Count Panel Data. In B. H. Baltagi (ed.) *Oxford Handbook of Panel Data Econometrics*. Oxford University Press.

Campbell, D. F., & Carayannis, E. G. (2014). Developed Democracies versus Emerging Autocracies: Arts, Democracy, and Innovation in Quadruple Helix Innovation Systems. *Journal of Innovation and Entrepreneurship 3*:12.

Castellani, D., & Fassio, C. (2019). From new imported inputs to new exported products. Firm-level evidence from Sweden. *Research Policy*, *48*(1), 322-338.

Carayannis, E. G., & Campbell, D. F. (2010). Triple Helix, Quadruple Helix and Quintuple Helix and how do knowledge, innovation and the environment relate to each other? A proposed framework for a trans- disciplinary analysis of sustainable development and social ecology. *International Journal of Social Ecology and Sustainable Development, 1*(1), 41–69.

Carayannis, E. G., & Campbell, D. F. (2009). 'Mode 3' and 'Quadruple Helix': toward a 21st century fractal innovation ecosystem. *International Journal Technology Management, 46* (3–4), 201–234.

Carayannis, E.G., Acikdilli, G. & Ziemnowicz, C. (2020). Creative Destruction in International Trade: Insights from the Quadruple and Quintuple Innovation Helix Models. *Journal of the Knowledge Economy 11*, 1489–1508.

Chakravorty, U., Liu, R. & Tang, R. (2017). *Firm Innovation under Import Competition from Low-Wage Countries*. CESifo Working Paper No. 6569, Center for Economic Studies and ifo Institute (CESifo), Munich. Retrieved February 18, 2022, from https://www.ifo.de/DocDL/cesifo1_wp6569.pdf

Coelli, F., Moxnes, A., & Ulltveit-Moe, K. H. (2022). Better, faster, stronger: Global innovation and trade liberalization. *The Review of Economics and Statistics*, forthcoming.

Colantone, I., Crino, R., & Ogliari, L. (2019). Globalization and mental distress. *Journal of International Economics*, *119*, 181-207.

Coucke, K. & Sleuwaegen, L, (2008), Offshoring as a survival strategy: evidence from firms in Belgian manufacturing. *Journal of International Business Studies 39*(8), 1261- 1277.

Crépon, B. & Duguet, E. (2007). Research and development, competition and innovation: Pseudo maximum likelihood estimation and simulated maximum likelihood methods applied to count data models with heterogeneity. *Journal of Econometrics 79*, 355-378.

Ding, S., Puyang, S. & Jiang, W. (2016). The effect of import competition on firm productivity and innovation: Does the distance to technology frontier matter? *Oxford Bulletin of Economics and Statistics 78*, 197-227.

Elayan, M. B., Hayajneh, J. A. M., Abdellatif, M. A. M., & Abubakar, A. M. (2022). Knowledge-based HR practices, π-shaped skills and innovative performance in the contemporary organizations. *Kybernetes*.

Geerts, A., Leten, B., Belderbos, R., & Van Looy, B. (2018). Does Spatial Ambidexterity Pay Off? On the Benefits of Geographic Proximity Between Technology Exploitation and Exploration. *Journal of Product Innovation Management, 35*(2), 151-163.

Guadalupe, M., Kuzmina, O. & Thomas, C. (2012). Innovation and Foreign Ownership. *American Economic Review*, *102*(7): 3594-3627.

Harhoff, D., Narin, F., Scherer, F.M. & Vopel, K. (1999). Citation frequency and the value of patented inventions. *The Review of Economics and Statistics 81*, 511-515.

Hayajneh, J. A. M., Elayan, M. B. H., Abdellatif, M. A. M., & Abubakar, A. M. (2022). Impact of business analytics and π-shaped skills on innovative performance: Findings from PLS-SEM and fsQCA. *Technology in Society, 68*, 101914.

Hummels, D., Jörgensen, R., Munch, J. & Xiang, C. (2014). The wage effects of offshoring: Evidence from Danish matched worker-firm data. *American Economic Review*, *104*(6), 1597-1629.

Lemmers, O. & De Wit, T. (2012). *Imports from China: from T-shirts to tablet PCs*. CBS webmagazine. Retrieved February 18, 2022, from https://www.cbs.nl/en-gb/news/2012/49/imports-from-china-from-t-shirts-to-tablet-pcs

Leten, B., Belderbos, R., & Looy, B. V. (2016). Entry and technological performance in new technology domains: Technological opportunities, technology competition and technological relatedness. *Journal of Management Studies, 53*(8), 1257-1291.

Li, X. & Zhou, M. (2017). Origin Matters: The Differential Impact of Import Competition on Innovation, in J. Alcácer, B. Kogut, C. Thomas, B. Yin Yeung (Eds.) *Geography, Location, and Strategy* (Advances in Strategic Management, Volume 36, pp. 387-427). Emerald Publishing Limited.

Liu, R., & Rosell, C. (2013). Import competition, multi-product firms, and basic innovation. *Journal of International Economics, 91*(2), 220-234.

Liu, Z., & Uzunidis, D. Globalization of R&D, Accumulation of Knowledge and Network Innovation: the Evolution of the Firm's Boundaries. *Journal of the Knowledge Econonmy 12***,** 166–182.

Martinez, C. (2011). Patent families: When do different definitions really matter? *Scientometrics 86*, 39-63.

Martin, Ph., Mayer, T. & Mayneris, F. (2011). Spatial concentration and plant level productivity in France. *Journal of Urban Economics 69*, 182–195.

Mayer, T., Melitz, M.J. & Ottaviano, G. I.. (2016). Product Mix and Firm Productivity Responses to Trade Competition. Review of Economics and Statistics, *103*(5) 1-59.

Min, Y. & Agresti, A. (2005). Random effect models for repeated measures of zero-inflated count data. *Statistical Modeling, 5*, 1–19.

Mion, G. & Zhu, L. (2013). Import competition from and offshoring to China: a curse or blessing for firms? *Journal of International Economics, 89*, 202-215.

Schumpeter, J.A. (1934). *Capitalism, Socialism, Democracy*. Harper, New York.

Shu, P., & Steinwender, C. (2019). The Impact of Trade Liberalization on Firm Productivity and Innovation. *Innovation Policy and the Economy 19*(1)*,* 38-68.

Smits, W., Vancauteren, M. & Weyns, I. (2018). Importconcurrentie en de vraag naar niet-routinematige arbeid. In: *Internationaliseringsmonitor 2018 II (pp. 93-109*). Statistics Netherlands, The Hague/Heerlen/Bonaire.

Statistics Netherlands. (2017). Patentaanvragen uit Nederland: een indicatie voor de kennisintensiviteit van de economie. In: *Internationaliseringmonitor 2017 III* (pp. 35-51). Statistics Netherlands, The Hague/Heerlen/Bonaire.

Suyker, W., De Groot, H., Bakens, J., Barell, R., Buitelaar, P., Choy, A., Rojas-Romagosa, H., & Toet, M. (2006). *China and the Dutch economy. Stylised facts and prospects. CPB Document 127.* CPB Netherlands Bureau for Economic Policy Analysis, The Hague.

Teece, D. J. (2007). Explicating dynamic capabilities: the nature and micro-foundations of (sustainable) enterprise performance. *Strategic management journal*, *28*(13), 1319-1350.

Tunc-Abubakar, T., Kalkan, A., & Abubakar, A. M. (2022). Impact of big data usage on product and process innovation: the role of data diagnosticity. *Kybernetes*.

Vancauteren, M., Melenberg, B., Plasmans, J., & Bongard, R. (2017). *Innovation and productivity of Dutch firms: A panel data analysis*. *Discussion paper*. Statistics Netherlands, The Hague/Heerlen/Bonaire. Retrieved February 18, 2022, from https://www.cbs.nl/-/media/_pdf/2017/44/innovation-march-2017j.pdf

Wooldridge, J. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics, 20*, 39–54.

Yamashita, N., & Yamauchi, I. (2020). Innovation responses from Japanese firms to Chinese import competition. *The World Economy, 43*(1), 60-80.

Yang, M.J., Li, N., & Lorenz, K. (2021). The impact of emerging market competition on innovation and business strategy: Evidence from Canada. *Journal of Economic Behavior & Organization, 181*, 117-134.

Zhang, L. (2017). *Escaping Chinese Import Competition? Evidence from U.S. Firm Innovation.* Retrieved February 18, 2022, from https://drive.google.com/file/d/11qmg7kcJuTjhTJb7fF4HjrNcXjyFhufe/view

Zhao, K. (2021). Competition of International Trade, Technology Spillover, and R&D Innovation. *Journal of the Knowledge Economy 12*, 676–694.

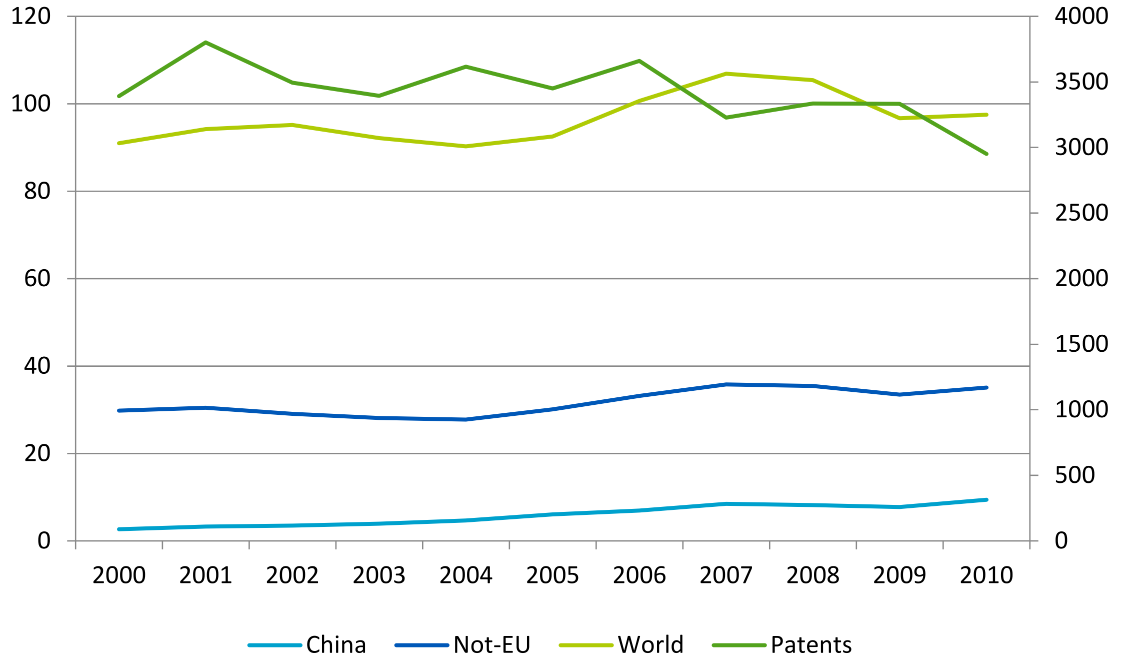
Appendix

Table A1. Industries in our analysis

Industry	**ISIC Rev 4.**
Manufacture of food products	10
Manufacture of beverages	11
Manufacture of tobacco products	12
Manufacture of textiles, wearing apparel, leather and footwear	13, 14, 15
Manufacture of wood products	16
Manufacture of paper	17
Printing and reproduction	18
Manufacture of coke and petroleum	19
Manufacture of chemicals	20
Manufacture of pharmaceuticals	21
Manufacture rubber, plastic products	22
Manufacture of building materials	23
Manufacture of basic metals	24
Manufacture of metal products	25
Manufacture of electronic products	26
Manufacture of electric equipment	27
Manufacture of machinery not elsewhere classified	28
Manufacture of cars and trailers	29
Manufacture of other transport	30
Manufacture of furniture	31

Figure and tables

Figure 1: Dutch patent applications to the European Patent Office and competing imports (constant prices) in manufacturing (right axis=# patents, left axis: import competition in million Euros)



Source: Eurostat.
China -> import competition from China
Not-EU -> import competition from not-EU countries
World -> total import competition

Table 1 Sample Means and Standard Deviations, 2000-2010

Summary statistics are of the overall sample of 1472 firms. There are 2313 observations for each of the variables.

Variable	Mean	Std. Dev.	Q1	Median	Q3
Patents application counts	7.827	97.540	0	0	1
Citations	1.055	2.061	0	0.005	1.150
Geographical scope	1.695	1.817	0	0	3.84
New patent entries	1.845	26.809	0	0	0
Import competition	0.416	0.187	0.287	0.433	0.557
Log Employment	5.594	1.387	0.483	5.614	6.484
Log R&D	6.296	2.724	5.771	6.905	8.389
Foreign Y/N 1/0	0.400	0.419	0	0	1
Number of activities	3.168	3.107	1	2	4
Number of firms	5.235	8.323	1	3	6
Log Domestic competition	0.334	0.608	1.210	2.202	2.822

Table 2 Summary statistics, 2000-2010 (Total sample; analysis sample is a subset)

Industry (ISIC Rev. 4)	NFirm	AR&D	AEmpl	APat	ACit1	ACit2	AImpC
Food (10-12)	388	9185	275	1.18	10.12	55.37	0.87
Textiles, clothing (13-15)	65	1341	152	0.26	1.27	4.30	-0.34
Wood, paper, printing (16-18)	192	2825	322	0.12	1.57	5.86	-0.34
Chemicals, pharmaceuticals (19-21)	198	23204	497	4.58	10.01	8.28	0.75
Plastics, non-metallic minerals (22-23)	292	1064	141	0.22	2.62	4.42	0.76
Basic, fabricated metals (24-25)	464	2660	160	0.24	2.81	4.49	0.44
Computers, electrical equipment (26-27)	176	83118	512	20.39	25.83	650.41	-0.29
Machinery, equipment n.e.c. (28)	684	9971	130	0.54	7.35	20.21	-1.01
Motor vehicles, other transportation (29-30)	160	9660	257	0.33	3.59	6.65	-0.11
Furniture, n.e.c. & recycling (31-33)	393	6689	138	0.28	3.13	8.76	0.17

Nfirm=number of firms per industry
AR&D=average R&D (in thousands of euros)
AEmpl=average employment
APat=10-year average patents for firms
ACit1=10-year average forward citations per patent
ACit2=10-year average forward citations per patent family
AImpC=Average change total import competition (in % points)

Table 3: Innovation and import competition

	Model 1, EPO patent counts		**Model 2, EPO patent counts**		**Model 3, Forward citations (Family)**		**Model 4, Domestic patents**		**Model 5, Geographical scope**		**Model 6, New entry patents**	
	Logit (Y/N)	Patent counts	Logit (Y/N)	Patent counts	Logit (Y/N)	Patent counts	Logit (Y/N)	Patent counts	Logit (Y/N)	Patent counts	Logit (Y/N)	Patent counts
Import competition in t-1	1.057*** (0.270)	1.115*** (0.326)	1.196** (0.285)	0.720** (0.335)	1.110*** (0.305)	0.994*** (0.353)	1.746*** (0.309)	1.336** (0.052)	1.127*** (0.286)	0.629*** (0.228)	1.576*** (0.357)	0.528 (0.396)
log(1+R&D per employee)in t-1	0.219*** (0.028)	0.267*** (0.031)	0.210*** (0.029)	0.246*** (0.030)	0.228*** (0.034)	0.143*** (0.028)	0.041* (0.023)	0.013*** (0.003)	0.224*** (0.030)	0.087*** (0.020)	0.283*** (0.040)	0.253*** (0.039)
Log(Employment)	0.198*** (0.054)	0.526*** (0.080)	0.287*** (0.058)	0.526*** (0.089)	0.370** (0.071)	0.217*** (0.067)	0.367*** (0.060)	-0.017* (0.009)	0.284*** (0.060)	0.194*** (0.045)	0.283*** (0.070)	0.411*** (0.111)
Log(Competition)			-0.033 (0.079)	-0.325*** (0.088)	-0.123 (0.087)	-0.074 (0.104)	0.013 (0.059)	-0.029* (0.015)	-0.030 (0.080)	0.050 (0.065)	0.000 (0.090)	-0.209* (0.097)
# Activities			0.204*** (0.054)	0.076 (0.061)	0.178*** (0.056)	0.188*** (0.053)	0.165*** (0.054)	0.015* (0.008)	0.205*** (0.053)	0.127*** (0.036)	0.247*** (0.061)	0.129* (0.074)
# Firms			-0.034*** (0.011)	-0.026** (0.010)	-0.039*** (0.012)	-0.033*** (0.009)	-0.023** (0.012)	-0.002 (0.001)	-0.036** (0.011)	-0.028*** (0.006)	-0.032** (0.013)	-0.032*** (0.012)
Foreign Y/N (1/0)			-0.322*** (0.104)	-0.324** (0.153)	-0.430*** (0.117)	-0.025 (0.126)	-0.859*** (0.086)	-0.000 (0.019)	-0.334*** (0.105)	-0.229*** (0.088)	-0.385*** (0.125)	-0.227 (0.190)
Intercept	-3.999*** (0.319)	-5.64*** (0.440)	-4.344*** (0.305)	-5.185*** (0.500)	-4.989*** (0.393)	-2.380*** (0.409)	-3.824*** (0.358)	-0.230*** (0.052)	-4.432*** (0.354)	-1.533*** (0.276)	-4.762*** (0.408)	-4.235*** (0.836)
alpha		3.602*** (0.301)		3.335*** (0.333)		4.177*** (0.301)		3.109*** (0.287)		4.441*** (0.241)		3.012*** (0.413)
Random effects	YES		YES		YES		YES		YES		YES	
Year dummies	YES		YES		YES		YES		YES		YES	
Log-likelihood	-4511.037		-4348.943		-3442.638		-3324.901		-4817.131		-3049.256	
# Observations	2313		2313		2313		2313		2313		1691	

Notes: Maximum Likelihood-estimates with (robust) standard errors in parentheses. Statistical significance is indicated by stars: *: 10%, **: 5%, ***: 1% significance level. All continuous control variables (except those in logs and counts) are bounded between the 1st and the 99th percentile. Reported in the logit equation is the change in probability (that patenting is positive) for a unit change in each of the explanatory variables.

Table 4: Innovation and import competition, by destinations

	Model 2, EPO patent counts		**Model 3, Forward citations (Family)**		**Model 4, Domestic patents**		**Model 5, Geographical scope**		**Model 6, New entry patents**	
Lagged import competition, by destination	**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**
China	5.710*** (2.130)	3.013 (2.380)	3.122 (2.424)	0.605 (2.614)	16.041*** (2.301)	0.872** (0.412)	4.299** (2.177)	2.899 (1.795)	4.501** (2.310)	1.986 (2.500)
Rest of the World	1.549*** (0.942)	4.093*** (1.084)	3.141*** (1.046)	3.748*** (1.199)	0.367 (1.023)	0.255 (0.177)	1.931** (0.967)	0.879 (0.821)	1.967* (1.183)	3.130*** (1.208)
EU countries	0.831** (0.376)	-0.413 (0.515)	0.411 (0.398)	0.051 (0.531)	1.535*** (0.395)	0.048 (0.072)	0.699* (0.377)	0.397 (0.266)	1.237*** (0.473)	-0.373 (0.653)
High-wage countries	1.255*** (0.309)	0.425 (0.401)	1.129*** (0.326)	0.877** (0.392)	1.574*** (0.325)	0.151*** (0.055)	1.196*** (0.311)	0.643*** (0.249)	1.749*** (0.391)	0.339 (0.504)
Middle-wage countries	0.997 (1.359)	4.00** (1.617)	1.304 (1.522)	2.767* (1.659)	3.802*** (1.411)	-0.193 (0.264)	0.798 (1.368)	0.527 (1.021)	0.731 (1.479)	2.450 (1.657)
Low-wage countries	56.867 (38.987)	74.455 (50.463)	40.842 (44.192)	37.178 (38.061)	62.429 (51.101)	10.693 (8.566)	58.328 (39.187)	8.111 (24.157)	98.844** (43.941)	20.160 (43.465)

Notes: Maximum Likelihood-estimates with (robust) standard errors in parentheses. Statistical significance is indicated by stars: *: 10%, **: 5%, ***: 1% significance level. All continuous control variables (except those in logs and counts) are bounded between the 1st and the 99th percentile. Reported in the logit equation is the change in probability (that patenting is positive) for a unit change in each of the explanatory variables.

Table 5: Innovation and import competition, Robustness results

		Model 2, EPO patent counts		**Model 3, Forward citations (Family)**		**Model 5, Geographical scope**		**Model 6, New entry patents**	
Variant		**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**	**Logit (Y/N)**	**Patent counts**
I. Controlling for foreign affiliates (period 2005-2010) (# obs. 1387)	Lagged import competition	1.540*** (0.367)	0.627 (0.419)	1.465*** (0.465)	1.132*** (0.405)	1.149*** (0.360)	0.865*** (.289)	1.508*** (0.358)	0.505 (0.398)
II. Controlling for export Y/N (1/0) (# obs.2313)	Lagged import competition	1.121*** (0.287)	0.669** (0.333)	0.891** (0.359)	0.882** (0.354)	1.052*** (0.288)	0.574*** (0.222)	1.464*** (0.360)	0.444 (0.397)
III. Poisson GMM with instruments (# obs.2313)	Lagged import competition	n.a.	1.553** (0.656)	n.a.	-.0.05 (0.455)	n.a.	1.207*** (0.226)	n.a.	0.851*** (0.219)
IV. Testing Lags (controls t-1) (# obs.1977)	Lagged (t-2) import competition and R&D	1.300*** (0.308)	0.474 (1.420)	1.240*** (0.336)	1.070*** (0.405)	1.287*** (0.311)	0.828*** (0.260)	1.676*** (0.354)	0.787* (.420)

Notes: Maximum Likelihood-estimates with (robust) standard errors in parentheses. Statistical significance is indicated by stars: *: 10%, **: 5%, ***: 1% significance level. All continuous control variables (except those in logs and counts) are bounded between the 1st and the 99th percentile. Reported in the logit equation is the change in probability (that patenting is positive) for a unit change in each of the explanatory variables.