Discussion paper

Import competition and firm innovation

Evidence from patenting firms in the Netherlands

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Content

Summary[1]

International trade has undergone rapid changes in the last decade: Eastern-European countries opened up, China joined the WTO, and these and many other countries, that initially played a minor role in international trade, have now become major competitors of traditional industrial countries. This paper analyzes the impact of import competition on patent activities by Dutch manufacturing firms for the period 2000-2010. Using a combination of patent, firm and trade data, we show that more intense import competition leads to a lower number of patent applications whereas it has no influence on the number of forward citations. For firms only engaged in domestic innovation, this negative import competition effect is more pronounced. Whereas most studies only consider import competition from China and other emerging markets, we also take high developed countries into account. We find that import competition from countries who were member of the EU before 2004 has a negative impact on the number of patents, whereas there is no statistically significant influence from newer EU member states, China or the group of countries in the rest of the world.

Keywords

Innovation, international trade, panel data

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1. Introduction

International trade has undergone rapid changes in the last decade: Eastern-European countries opened up, China joined the WTO, and these and many other countries that initially played a minor role in international trade have now become major competitors of traditional industrial countries.

In this paper, we explore how import competition from the rest of the world has affected innovation in the Netherlands. Theoretically, exposure to import competition, as a result to open markets, may 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 which 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 and therefore “remains intrinsically an empirical question” (Autor et al., 2016).

The most recent line of research 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. Therefore, our analysis extends import competition for a firm also from high-wage countries. So far, we have 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 which could also have varying impact on innovation. For instance, Amiti and Khandelwal (2013) document significant quality differences among products imported by the U.S. from countries of various income levels. Li and Zhou (2017) find that, high-wage import competition led U.S. firms to increase their innovation activities, while in contrast import competition from low-wage countries did not always lead to more innovation activities. In other words, there is a lot of heterogeneity.

In this paper, we explain firm-level innovation activities using patent data. Patent data, used to establish the link between import competition and innovation, has some distinct features. The use of patents ensures firms with ex ante incentives for inventive activities by granting ex post monopoly rights to benefits from such activities. A firm may use its patenting rights in function of market competitive reasons such as exclusion of competitors, strategic licensing, or joint-ventures. Indeed, a firm’s decision to patent a certain innovation can be considered as a “strategic decision”. Not all innovations are patented. Because the contents of patent applications are disclosed, this may benefit existing and potential competitors. Some firms consider strategically unused patents to prevent other firms using the patented technology. In addition, patents may also be kept for future license negotiations of for future production and sales activities. For instance, a paper by Hussinger (2006) provides evidence that firms may use secrecy when developing a new technology, but then apply for a patent when the new product is about to be commercialized. To a certain extent, this means that results confirming a positive or negative relationship between import competition and innovation to certain extent may also be caused by the choice of firms of considering unused patents to prevent other firms getting access to the patented technology. Because the innovation literature postulates that R&D and patent behavior of firms are complements[2], it is not a surprise that competitive effects linked to R&D follow a same (positive or negative) pattern. We employ data not only about patent applications (and forward citations) on a European level, mostly the larger firms, but also patent applications on Dutch level to capture innovation activities of a large group of SMEs as well. This allows us to control for capturing additional firm heterogeneity in terms of patent activities related to firm size and economic international activity.

Next to the main contributions of assessing the impact of import competition on innovation, this paper also puts some attention to measurement. We note that the level of analysis in this paper is the enterprise group since that is the entity where we can link the patent counts properly. Then, we take the composition of this group in the Netherlands into account. It may consist of different enterprises, each of them with a different main activity or not. We take the number of enterprises into account, the number of main activities and we derive the import competition for an enterprise group by weighting the import competition for the activities of each of its enterprises. The weights are the number of employees at the enterprises. In our opinion, this gives a better estimate of the true import competition than the import competition based solely on the main activity of the whole enterprise group. We slightly distress from the approach of Autor et al. (2016) 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 it is 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 that 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. [3]

[2] We refer to Peters (2009) and Raymond et al. (2015) who use respectively patent applications and new product sales as two forms of output innovations.

[3] 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

The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature. Section 3 describes data and methods, 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. Background

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 is according to some recent work subject to the same theoretical predictions 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). [4]

For local firms, import competition leads to a shrinking market share. There is a large literature on how an expanding market size might increase innovation because innovation is complementary to the firm's decision to export (Costantini and Melitz, 2007 and Bustos, 2011), but this argument does not apply in the case of new import competition because market share (and the corresponding size) is shrinking. Innovation in the face of new import competition must be driven by something other than increases in firm scale.

The papers of Bloom et al. (2013, 2016) 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

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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.

[4] 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 high competitive level, the innovation incentives of the follower are low because his profits are zero anyways.

‘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, indirectly boosting 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. Among the most recent contributions, 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. These results are similar to those of Arora et al. (2015), who find a positive relationship between import competition and patenting.

These results, however, are in contrast with Autor et al. (2016). 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 from 1991 to 2007 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 15 log-point decrease in patents. Using data from the 1975 to 1991 period and a regression setup that accounts for the diverging secular innovation trends in the computer industry and the chemical industry, the study confirms that firms in China-exposed industries did not already have a weaker patent growth prior to the arrival of the competing imports. The negative impact remains robust not only for firm’s patenting behavior but also for its global employment, global sales and global R&D expenditures.

The most recent line of research 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. 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. In a recent paper, Bombardini et al.

(2018) also build upon a framework of Aghion et al. (2005) and 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 U.S. from countries of various income levels. Li and Zhou (2017) find that, high-wage import competition led U.S. firms to increase their innovation activities, while in contrast import competition from low-wage countries did not always lead to more innovation activities. In addition, these innovation promoted effects are especially found on firms that are close to the technological frontier. In other words, there is a lot of heterogeneity.

Using Chinese firm-level and international transaction data being linked to US industry data for the period 2000-2006, Ding et al. (2016) 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. The authors note that imports from high-income 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-income countries promotes innovation while foreign competition from low wage countries has no statistically significant effect.

3. Data construction

Our data consists of an unbalanced panel of over 2400 firms situated in the Netherlands, during the period 2000-2010, representing the population of firms that have applied at least for one patent during the years 2000-2010. 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 penetration.

3.1 Patents and firm-level data

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). This patent data gives us information such as the application number, the patent owner (name of the firm), patent title, name of the inventor, publication year and location. However, firms may register patents or report R&D expenditure 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). [5]

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 developments 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 consider two types of forward citations. First, we calculated the number of forward patent citations by later patents, issued from all patent granting authorities available in PATSTAT (European Patent Office (EPO), US Patent and Trademark Office (USPTO), Japanese Patent Office (JPO)), for all EPO patent applications for each sample firm ("Citations1").

In the second definition 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, being defined as 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 to extent to which firms are involved with the internationalization of technology, and 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 ("Citations2"). The forward citation data is restricted to all patents granted up to the year 2010 with forward citations until autumn 2016. [6]

These firms are then matched to a subsample of firms from which R&D is reported. 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. [7] The R&D surveys

[5] We refer to Vancauteren et al. (2017) for a more detailed description of the data. The 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.

[6] See Martinez (2011) for a recent overview on the various definitions that are applied using the PATSTAT patent citation database.

[7] 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.

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 industry category assignment scheme which we use throughout this paper, based on ISIC Rev. 4 codes, is presented in table A1.

3.2 International trade data

This section first explains the data sources that were used to construct the measure to capture international competition. Namely, international trade data and statistics from National Accounts about trade and turnover. Then it will explain how the measure of import competition was constructed.

Data about Dutch trade in goods is collected from several sources. Smaller traders within the European Union do not have to report their trade in detail to Statistics Netherlands; their total trade is known due to VAT reports and the detail is estimated. Larger traders within the EU have to report their trade in detail (country and the products in the Combined Nomenclature, a further development of the World Customs Organization's Harmonized System nomenclature). Trade outside the European Union is collected by the customs office where large traders might send the data to Statistics Netherlands directly. This is also in detailed country and product level.

National Accounts uses the same data about trade in goods, but has many different other sources to create a complete image of the Dutch economy. For example, it also uses the turnover statistics and the detailed statistics about production of manufactured goods (PRODCOM). It harmonizes concepts and classifications and integrates the data to obtain a consistent view. Furthermore, it keeps data comparable through time.

Estimating direct import competition

In order to measure import competition, we follow the idea of Autor et al. (2016). They set

$$\Delta(Import\ competition\ from\ China\ in\ industry\ j\ in\ year\ t)$$

$$= \frac{M_{j,t}^{China} - M_{j,t-1}^{China}}{Y_j + M_j - X_j}$$

Here M_j^{China} are the imports from China of products of industry j, Y_j is the production of industry j, M_j the imports of products of industry j and X_j the exports of products of industry j in the year 2000. To arrive at these estimates, Autor et al. match the commodity codes of trade to industries, match the international trade data to industries, aggregate imports and exports by country (if necessary) and by industry. Autor et al. use the turnover statistics by industry to measure its production.

We slightly digress from the approach of Autor et al. and do not use the trade and industry data, but use similar data from the national accounts statistics instead. We do this for the following reasons:

- About half of Dutch trade in goods considers of re-exports (Statistics Netherlands, 2016), who do not form competition for sales on the domestic market. The trade statistics do not yet have good information about the value of the products that are imported for the domestic market.
- National accounts integrates the data from all different statistics and makes it consistent, since it is known that there are sometimes discrepancies between turnover and exports, purchases and imports.
- During the time period under concern, 2000-2010, both the turnover statistics and trade statistics changed concepts, definitions and methods. For example, a transition to a new industry classification (ISIC Rev. 3 to ISIC Rev. 4) or a different delineation of re-exports and transit trade. Since the major aim of these statistics is to measure the current situation, they did not repair the time series. Because a major aim of the national accounts is to have comparable numbers through time, it did repair the time series.

We arrive at the numbers Y_j, M_j, X_j and $M_{j,t}^{China}$ in the following way. First we delineate which industry produces which products and to which industry belong the individual products. We match the imported goods (with country detail) to these individual products and the corresponding industries. This yields competing imports. We use constant prices with base year 2010. Below it is explained in more detail.

- Consider all manufacturing industries (ISIC Rev. 4: the industries 10-33) except “manufacture of other products” and “repair and installation of machinery” (in ISIC Rev. 4 these are the industries 32 and 33). We exclude the last two industries because in the Netherlands a large part of “manufacture of other products” consists of sheltered workshops and since repair and installation does not produce goods itself. The industries that manufacture textiles, wearing apparel, leather and footwear (in ISIC Rev. 4 these are the industries 13, 14, 15) are aggregated to one industry since they are rather small in the Netherlands. We arrive at a total of 20 industries in total, shown in table A1. From the database of national accounts the value (in current and constant prices) of production for 81 different industrial goods[8] is obtained, and the industry where it was produced. Some of these commodities are produced in several industries. We then assign the good to that industry that produces the most of this good[9].

[8] An aggregation by Statistics Netherlands of the Classification of Products by Activity (CPA) of the EU.
[9] With exception of the printing and reproduction industry, the ratio of (value of goods of this industry that were assigned to this industry) / (value of total goods) was usually over 90 per cent in each industry. In other

- Y_j, total production of industry j, is extracted from the same database of national accounts.
- Subsequently, we obtain from this database the value of imports, imports for re-exports, exports and re-exports of each good. We remove imports for re-exports and re-exports from the trade flows. 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; these are respectively the import competition for industry j and its exports.
- The value of imports of each good from China follows from the trade statistics. We match the commodity codes from the trade statistics to those of national accounts using a concordance table that is used in the regular process of national accounts. Aggregating imports from all countries for products of industry j yields a number similar to M_j. However, it might differ from the value M_j in national accounts due to different concepts, integration of different statistics and so on. To remain consistent with national accounts, we scale, on product level, the value from the trade statistics to the value M_j of national accounts. To arrive at the number $M_{j,t}^{China}$ we first scale, on product level, imports from China with the same factors. Then we aggregate the product by industry[10]. Estimates for competing imports from other countries are obtained in a similar way. Because the data on imports do not yet contain good information about their destination (use on the domestic market or re-exports) we have to assume that the distribution among countries is the same for total imports (which is known) and of imports for use on the domestic market (which is unknown).

Note that in this way (just as in Autor et al.) we measure import competition for the main products of industry j. If an industry j would produce by-products that are usually made in another industry k, we do not consider the imports of these products as competing imports for industry j but only for industry k. For example, if the car industry would produce a small value of metal bars, large (or small) imports of metal bars would be considered competing imports for the metal industry only but not for the car industry.

To estimate import competition for an enterprise group, we take its composition into account. We do this by calculating the import competition for each of the industries of the underlying enterprises, and then weigh these results on industry level using employment at each firm as a weight to arrive at import competition for the whole enterprise group. In this way we take the heterogeneity between enterprise groups into account, since their underlying firms might be active in different industries than the enterprise group itself. Adding the import competition from individual countries yields the import competition from this group of countries.

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words, in most industries the by-production is low. Furthermore, a product that is assigned to an industry is hardly produced elsewhere as a by-product.

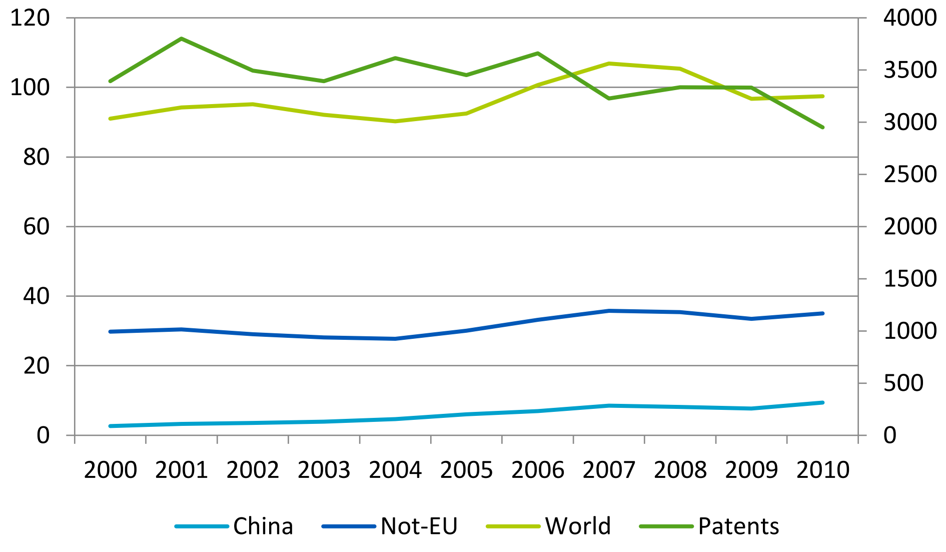
[10] Example: say trade statistics has 110 million of imports of tablets, of which 55 million from China, and national accounts has 100 million of imports of tablets. Then the rescaled number $M_{j,t}^{China}$= 100/110 * 55 million = 50 million.

3.3 Data characteristics

In this section we highlight some overall trend characteristics on patenting and import competition activities over our sample period before we turn to our micro-econometric analysis. Figure 3.3.1 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.

The major import competitor of the Netherlands in 2010 was Germany, which exported a total of 24.2 billion euros of goods that were destined for the Dutch market. Followed by Belgium (12.8 billion euros), China (9.5 billion), United States (6.2 billion), United Kingdom (5.9 billion), France (5.1 billion), Japan (3.4 billion), Italy (3.0 billion), Spain (2.7 billion) and Sweden (2.3 billion euros). Germany and Belgium were the top 2 import competitors throughout our sample period. It is noteworthy that, following China's entry into the World Trade Organization (WTO) in 2001, China has risen from the 7th spot in 2001 to become the third largest import competitor in 2010. The Chinese share in total import competition has increased from 3.5 percent in 2001 to 9.2 percent in the year 2010.

3.3.1 Dutch patent applications to the European Patent Office and competing imports (constant prices) in manufacturing



Source: Eurostat.

Table 3.3.2 presents the number of patent applications by major manufacturing groups for the whole period using total population data available from Statistics Netherlands. The stark differences in the sectorial trends are very apparent. The highest number of patent applications came from the computer and electrical equipment industry. This industry had 1294 patent applications in the year 2010. The number of patent applications in this industry increased throughout the years 2000-2003, before steadily decreasing in the years 2004-2010. However, this industry still remained the most innovative in terms of patent applications throughout the sample period. The food industry also faced a noteworthy decline in patent applications, with a major dip in the 2004-2006 period and only 55 applications in the year 2010 compared to 360 applications in the year 2000. The number of patent applications in the other manufacturing sectors changed more modestly over time.

3.3.2 Patent applications to the European Patent Office by the Dutch manufacturing sector

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Industry (ISIC Rev. 4)	#										
Food (10-12)	360	339	334	208	165	182	130	303	267	261	55
Textiles, clothing (13-15)	8	7	9	9	10	6	18	11	7	7	16
Wood, paper, printing (16-18)	33	20	17	10	11	13	11	18	14	17	6
Chemicals, Pharmaceuticals (19-21)	422	470	421	448	711	494	622	607	611	645	516
Plastics, non-met. minerals (22-23)	40	38	36	46	40	36	53	53	45	40	29
Basic, fabricated metals (24-25)	76	65	53	69	76	78	65	71	82	56	58
Computers, el. equipment (26-27)	1623	1916	2547	2721	2395	2452	2077	2096	1510	1872	1294
Machinery, equipment n.e.c. (28)	191	209	199	315	305	223	231	146	214	209	188
Motor vehicles, transport (29-30)	54	47	30	36	22	19	27	39	26	28	33
Furniture, n.e.c. & recycling (31-33)	46	58	47	53	37	75	100	101	61	48	43

Note: author’s computations

The differences across industries are also very apparent when considering the import competition at industry level. Table 3.3.3 shows per year competing imports divided by the total (domestic and foreign) supply of goods destined for the Dutch domestic market, expressed in percentages. This ratio gives us an impression of which industries face the highest exposure to foreign import competition. Both the numerator and denominator of this ratio are measured using constant prices from the year 2000. The industries facing the highest import exposure throughout the years are the computer industry, the electrical equipment industry and the motor vehicles and other transportation industries. These industries faced an import exposure of more than 60 percent in the year 2010, which means that the Netherlands imported roughly two times the amount it produces itself for its domestic market. However, if we look at the changes in import exposure over the years, then we notice that the sharpest decline was in the machinery and equipment industry, where the import exposure has declined from 60 percent in 2000 to 44 percent in 2010. At the industry level depicted in table 3.3.3, no industry has faced a large incline in import exposure over the years.

3.3.3 Exposure to import competition on industry level

Industry (ISIC Rev. 4)	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
	%										
Food (10-12)	30	31	31	30	30	30	31	31	31	32	33
Textiles, clothing (13-15)	37	38	37	38	37	36	37	35	34	31	35
Wood, paper, printing (16-18)	35	33	33	33	32	30	30	31	29	28	29
Chemicals, Pharmaceuticals (19-21)	57	52	54	52	50	48	49	48	44	42	45
Plastics, non-met. minerals (22-23)	46	46	46	44	44	44	44	44	44	46	48
Basic, fabricated metals (24-25)	37	40	41	38	36	36	38	38	37	36	35
Computers, el. equipment (26-27)	67	65	65	63	61	64	64	65	63	61	65
Machinery, equipment n.e.c. (28)	60	55	64	61	59	59	60	57	51	46	44
Motor vehicles, transport (29-30)	80	74	76	78	77	78	80	78	75	73	70
Furniture, n.e.c. & recycling (31-33)	40	41	40	40	41	39	39	39	36	40	43

Note: author's computations

Exposure to import competition is defined as competing imports divided by total supply for domestic market, both in constant prices. It is expressed in the table in percentages.

4. Empirical implementation

We estimate a similar model specification to 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 and we find for many firms zero patent counts during some of the years, or, if applied (whether granted or not), the zero citation patent counts also occur for firms that received no forward citations.[11]

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 such as 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. [12] Let a firm be indicated by the subindex i, industry be indicated by the subindex j and time be the subindex t. We first introduce

[11] We observe that 60% of our sample includes panel-year firms with zero patent applications. Similarly, Bound et al. (1984) observe for the U.S. 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.

[12] Our model with reference to the innovation stage draws heavily from Vancauteren et al. (2017). The author uses a static random effects Hurdle model controlling for zero inflation. As a robustness check a zero-inflated model is also estimated.

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

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

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

where IC_{it} is the growth 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 and 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 δ1, β1 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 $\boldsymbol{X}_{\mathbf{1it}}$). 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 follow 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. So we might expect different decision criteria concerning the first patent and additional patents.

We model the probability pit as,

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

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). [13]

To explain patent activities we include in the vector $\boldsymbol{X_{1it}} = \boldsymbol{X_{2it}}$ 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"), the number of firms being a variable indicating the number of domestic firms in the enterprise group under concern ("number of firms"), a variable indicating the number of industries of enterprises within the enterprise group ("number of activities"), a dummy variable indicating whether a firm is under foreign control of domestically owned ("Foreign Y/N 1/0"), and domestic competitive pressure ("competition"). We now explain the last two variables. 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. To calculate how local competitive pressure affect a firm's patenting behavior, we follow Martin et al. (2011) and measure the level of 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 competition 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).

5. Empirical results

5.1 Baseline results

Before we discuss the regression results, summary statistics of our key variables (in the transformation used in the analysis) are shown in table 5.1.1. The statistics are based on the total sample of firms from the period 2000-2010. The overall sample consists of 2294 panel firm-year observations. The number of firms is 1472.

[13] For a detailed discussion on the zero-dominance in count models we refer to Cameron and Trivedi, 2013.

5.1.1 Sample Means and Standard Deviations, 2000-2010

Variable	Mean	Std. Dev.	Q1	Median	Q3
Patents	1.712	0.361	0	0	1.999
Citations1	1.508	0.370	0	0	1
Citations2	2.009	0.243	0	0	2.534
Import competition	-0.002	-0.045	-0.011	0.008	0.013
Log Employment	5.668	-1.416	0.483	5.614	6.484
Log R&D	7.08	-3.141	5.771	6.905	8.389
Foreign Y/N 1/0	0.41	-0.492	0	0	1
Number of activities	3.22	-3.173	1	2	4
Number of firms	5.40	-5.597	1	3	6
Log Competition	2.79	-0.665	1.21	2.202	2.822

The unweighted average firm in our sample applies approximately for 1.7 patents a year, with an average forward citation count of 1.5 and 2, spends on average e7.08 * 1000 = 1.2 million euros on R&D. On average the annual change in import competition is equal to -0.002 (-0.2 percent), 41% of the panel firms have a foreign parent, firms are on average involved in 3.2 industries and consist of 5.4 enterprises. The average annual competition is e2.790 = 16, corresponding to a Herfindahl index of 1/16. The distribution of the patent variables is quite skewed, while most of the other variables are more evenly spread. Table 5.1.2 provides similar summary statistics, now by industry.

5.1.2 Summary statistics (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)

We now consider the estimates of the patent equation discussed in section 4. Table 5.1.3 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., H0: alpha=0), is conclusively rejected. As a consequence, we only report the outcomes based on the Negative Binomial distribution. Three variants have been estimated. In column I we report, using the Hurdle model, the Maximum Likelihood based results of the number of patent applications, without 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 column II, we present the same model including the entire unobserved heterogeneity. In column III we present the full model. In the table we present the results with lagged import competition and lagged R&D included, but results do not change dramatically once we replace the lagged import competition effect with an instantaneous effect (not reported).

5.1.3 Patents and import competition[14]

	I Logit (Y/N)	Patents	II Logit (Y/N)	Patents	III Logit (Y/N)	Patents
Lag (Import competition)	-1.809*	-2.986***	-1.782*	-3.091***	-2.124**	-2.850***
	(1.032)	(1.105)	(1.021)	(1.135)	(1.066)	(1.113)
Lag (log (1+R&D per employee))	0.223***	0.275***	0.230***	0.281***	0.222***	0.253***
	(0.027)	(0.029)	(0.028)	(0.031)	(0.029)	(0.030)
Log(Employment)	0.301***	0.661***	0.198***	0.545***	0.263***	0.535***
	(0.046)	(0.061)	(0.054)	(0.079)	(0.058)	(0.087)
Log(Competition)					-0.081	-0.358***
					(0.079)	(0.087)
# Activities					0.176***	0.076
					(0.051)	(0.061)
# Firms					-0.034***	-0.026***
					(0.011)	(0.010)
Foreign Y/N (1/0)					-0.273**	-0.313***
					(0.104)	(0.153)
Intercept	-3.841***	-5.562***	-3.531***	-5.232***	-3.723***	-4.887***
	(0.272)	(0.360)	(0.282)	(0.398)	(0.305)	(0.429)
alpha		3.658***		3.593***		3.320***
		(0.316)		(0.299)		(0.333)
Random effects	NO		YES		YES	
Year dummies	YES		YES		YES	
Log-likelihood	-5252.186		-5266.037		-4530.234	

We find that the parameter estimates for import competition are statistically significant and negative 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 are decreasing with increasing import competition. The coefficient of –1.809 in model I at "Logit(Y/N)" indicates that an increase in import competition by one percentage point is estimated to decrease the patent propensity by 1.809 percentage points. The coefficient of -2.986 in the column next to it, at "Patents", indicates that a one percentage point increase in import competition leads to a firm applying for 2.986 patents less. We see that including random effects, capturing the unobserved ability to be innovative, hardly affects the estimation results with the exception of employment. The import competition effect remains robust across specifications. The coefficients of the log of employment are always

[14] 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.

positive, indicating that the propensity to patent and the number of patents are increasing with firm size. In addition, more R&D per employee and more different activities in the same enterprise group are positively related to the propensity to apply for a patent and to the number of patents. The number of enterprises in the enterprise group and foreign ownership however, are negatively related. Competition seems to play a negative impact on patenting therefore suggesting that as competition increases, firms are less engaged with their patent applications.

5.2 Patent quality

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, among other variables. According to Bloom et al. (2016), more intense import competition translates, at one hand, into an increase of the quality of innovation due to a reallocation effect toward firms with high productivity levels which tend to be also more innovative. On the other hand, import shocks might induce a reallocation of resources toward the more technologically advanced firms, indirectly boosting resource allocation to higher innovation activity. Mion and Zhu (2013) and Bloom et al. (2016) find that in response to greater import competition firms (respectively in Belgium and EU wide) upgrade their innovation quality.

In order to test this, we adopt the same specification as in column III of table 5.1.3, where the dependent variable is measured by either the total number of forward citations per patent (column I) or (column II) by the number of forward citations by later patents that belong to the same patent family. The results are presented in table 5.2.1.

Our results are that when patent citations are used as an indicator for the technological importance of the patent, the coefficient on the effect of import competition becomes in general insignificant across specifications. In other words, on average import competition does not lead to better or worse patents. We do find that in the propensity patent part of the model, the propensity to have a cited patent is decreasing with more intense import competition. What does have 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.

5.2.1 Citations and import competition[15]

Variables	I Logit (Y/N)	Citations1	II Logit (Y/N)	Citations2	III Logit (Y/N)	Domestic patent
Lag (Import competition)	-3.229**	0.710	-0.174***	0.452	-4.939***	-6.432***
	(1.398)	(1.889)	(1.169)	(1.830)	(1.193)	(1.335)
Lag(log(1+R&D per employee))	0.186***	0.212***	0.241***	0.250***	0.058**	0.122***
	(0.035)	(0.037)	(0.034)	(0.032)	(0.023)	(0.025)
Log(Employment)	0.445***	0.448***	0.326**	0.547***	0.340***	0.592***
	(0.081)	(0.100)	(0.070)	(0.091)	(0.060)	(0.064)
Log(Competition)	-0.249***	-0.115	-0.174**	-0.463***	0.013	0.122
	(0.094)	(0.138)	(0.080)	(0.138)	(0.086)	(0.087)
# Activities	0.098*	0.098	0.152***	0.064	0.144**	0.043
	(0.052)	(0.103)	(0.052)	(0.096)	(0.050)	(0.057)
# Firms	-0.036***	-0.033**	-0.041***	-0.025**	-0.028**	-0.020
	(0.013)	(0.013)	(0.012)	(0.012)	(0.011)	(0.012)
Foreign Y/N (1/0)	-0.456***	-0.143	-0.342***	0.124	-0.743***	-1.003***
	(0.134)	(0.224)	(0.115)	(0.201)	(0.117)	(0.127)
Intercept	-5.161***	-3.197***	-4.349***	-3.120***	-2.974***	-4.202***
	(0.418)	(0.565)	(0.349)	(0.494)	(0.299)	(0.331)
alpha		12.799***		9.982***		3.769***
		(1.075)		(0.660)		(0.287)
Random effects	YES		YES		YES	
Year dummies	YES		YES		YES	
Log-likelihood	-3171.541		-4677.013		-3218.011	

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. Amiti and Khandelwal (2013) show that there is a significant relationship between import tariffs and innovation, whose direction depends on the quality of the product. For high quality products, low tariffs (higher import competition) stimulate innovation, for low quality products, low tariffs discourage innovation (quality upgrading). Ding et al. (2016) find supporting evidence in this direction by showing that import competition from high-wage countries leads to higher TFP growth and innovation. The authors hypothesize that imports from high-wage countries are usually characterized by higher technology, which in turn lead domestic firms to engage in more innovative activities in order to offset such import competition.

The results in table 5.3.1 indicate that more import competition from the EU leads to a smaller propensity of applying for patents and also to a smaller number of patent applications. An analysis with two parts of the EU, namely the countries that were members of the EU before 2004 and those that joined the EU in the time period 2004-2007, suggests that this is due to the old member states and not to the newcomers. However, for China and the Rest of the World there are no (statistically significant) implications of import competition. There is no

[15] 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.

(statistically significant) impact of import competition from the EU, China or Rest of the World to the quality of the patents measured by the number of citations of patents.

5.3.1 Patents and import competition, by destination[16]

Lagged import competition by destination	I Logit (Y/N)	Patents	II Logit (Y/N)	Citations2	III Logit	Patents
China	-2.383	-1.290	-3.852	-8.226	-2.421	-0.346
	(8.663)	(9.083)	(13.060)	(12.311)	(8.756)	(9.185)
Rest of World[17]	0.039	-1.356	-0.722	2.276	0.075	-1.445
	(2.501)	(2.350)	(3.154)	(4.006)	(2.491)	(2.365)
EU total	-3.285**	-3.729**	-4.628***	-0.452		
	(1.640)	(1.578)	(1.970)	(3.049)		
EU New					-8.949	20.138
					(14.261)	(21.307)
EU Old					-3.004*	-4.999***
					(1.755)	(1.737)

We note that we also considered a similar analysis but consider import destination country groups according to low wage, medium and high wage countries as by the World Bank (see table A2). The results are similar, that is, only the coefficient of import competition originated from high wage countries is negatively significant with a magnitude of -2.1 when considering patent counts.

5.4 Dutch versus EPO oriented patenting activities

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 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 a both offices jointly; however, the patent data is constructed in such a way that it prevents this double counting of inventions. The EPO versus national distinction is also suited to analyze the internationalization and the valuation of innovations. Firms that seek international patents protection and are internationally active, are willing to overcome these higher transaction costs if

[16] 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.
Not shown in the table are the estimates for the variables as in tables 5.1.3 and 5.2.1, namely lag (Log(1 + R&D per employee)), Log(employment), Log(competition), number of activities, number of firms, foreign ownership yes/no, intercept, random effects and year dummies. Due to lack of space only the results for "Citations 2" and not those for "Citations 1" are shown.

[17] EU Old is the group of 14 countries that, together with the Netherlands, formed the EU at 1-1 2004: Belgium, Luxembourg, France, Germany, Italy, Spain, Portugal, Sweden, Austria, Denmark, United Kingdom, Finland, Ireland and Greece.
EU New is the group of 12 countries that joined the EU in 2004 and 2007: Romania and Bulgaria. We did not include Croatia since it joined the EU in 2013, after the time period 2000-2010 in the study.
Rest of World is the world minus China minus EU Old and minus EU new.

benefits exceed costs. In addition, it has also been shown that the most valuable patents are those that include filings in major international markets. In comparison to EPO patents, the firm distribution of national patent data is more evenly spread throughout firm size distribution.[18] The results summarizing the impact of import competition on the number of local patent applications are listed in the very last column, table 5.2.1.

The nature of the results is comparable to that of those in table 5.1.3, about the patents applied at the European Patent Office. Namely, import competition, foreign ownership and the number of enterprises in the enterprise group are related to a smaller propensity to apply for patents and a smaller number of patents, whereas more R&D expenditures and more different activities within the enterprise group are related to a higher propensity to apply for patents and more applications. More different activities within the enterprise group are also related to a higher propensity to apply for patents. On the number of domestic patents, the size of the coefficients for import competition is much larger than in table 5.1.3. For example, an increase of 1 percentage point in import competition for a given enterprise group will on average lead to a decrease in European patent applications of 3, but a decrease in Dutch patent applications of 6.

6. Further Robustness checks

6.1 Down- and upstream sectors

The previous results all concerned the effects of (lagged) import competition on the industry that produces the same good as the competing imports. However, as we explained before, other industries might be affected as well. Namely, those industries that are either upstream or downstream in the value chain of the producing industry. Not taking into account the upstream and downstream competition effects might result in omitted variable bias. [19]

This import competition direct upstream and downstream is a weighted average of trade exposure changes. As Murray (2017) explains, for direct upstreamness of an

[18] We refer to Vos (2017) for a detailed firm-patent descriptive analysis.

[19] One paper that investigates the effect of downstream import competition on patents, which is closely related to the current paper, is Liu and Qiu (2016). The authors investigate the effect of intermediate input imports on Chinese firms' patent filing from 1998 till 2007. The downstream import competition effect is measured by a reduction in import tariffs weighted by cost shares using input-output tables. Turning to the results, it is found that input tariff reductions reduce patent innovations of Chinese firms. Taking heterogeneity effects into account, these negative effects of intermediate input imports are more pronounced for firms that are closer to the technological frontier. Empirical evidence also shows that in response to tariff cuts, firms opt for importing high-quality intermediates, whereby reducing innovations. Literature that combines the two strands, namely taking the origin of competition into account and including indirect effects, is scarce. Sachs et al. (1994) consider the trade effects on U.S. employment, by skill, and discern by trade with a developing country and trade with a developed country. They use input output tables to estimate the direct and the indirect effect and add them to arrive at the total. Federico (2014) analyses the effect of competition from low-wage countries on domestic activity and finds significant effects of competition through inter-industry linkages.

industry i this is for industry i's buyers and the weights are the shares of industry i's output purchased by those buyers. Whereas for direct downstreamness of an industry i, this is for industry i's suppliers and the weights are the shares of the supplier's gross outputs purchased by industry i. Murray also explains how to extend these measures to buyers and suppliers more upstream and downstream in the value chain and we followed his approach (see A3 in the appendix for technical details). Besides import competition upstream and downstream we took the same explaining factors into account as in the previous models, for example Log (employment) and number of firms in the enterprise group.

The results that we have discussed so far are not affected when including up- and downstream effects (simultaneously or separated as either up- or downstream). For instance, using the specification in column III of Table 5.3.1 where we look at origins of import competition, the negative coefficient on import competition from the EU changes from -4.999 to -4.881 when we augment the equation with the three upstream variables on import competition according to the same regions (Rest of World, China, old and new EU) and the coefficient changes from 4.999 to -5.041 when we augment the equation with the downstream effects.[20] We note that, in general, the coefficients of upstream and downstream are not statistically significant, neither for the propensity that a firm is applying for a patent nor for the number of patent applications. The only two exceptions are, on the 10 percent significance level, for the number of patents in upstream enterprise groups. The number of patents in an upstream enterprise group in a given year is 10.7 lower when the total import competition was one unit lower in the previous year. The results indicate that this is caused by the import competition from high wage countries. One unit more competition from high wage countries in a given year leads to 14.1 less patents in the next year, and this is statistically significant on the 10 percent significance level. Whereas the import competition from low wage countries is not statistically significant at all. Note that our results for direct import competition (table 5.3.1) also pointed in this direction: only imports from high wage countries influence innovation, not the propensity to apply for a patent, but the number of patent applications.

However, we also note that the numbers of the up- and downstream competition effects are very high (over 100) in several cases. This casts doubts on the model in this specific case; it might not be appropriate. This is in contrast to the results of Murray (2017) who finds that the effects of upstream and downstream import exposure are of the same magnitude (albeit smaller) as direct import exposure.

6.2 Endogeneity

Previously, we found that the impact of a positive change in import competition on patents is negative. However, potential endogeneity problems may arise with R&D and the import competition variables. Endogeneity may arise from omitted variable bias as there are many possible missing or unobservable factors when

[20] Results on robustness are available upon request.

explaining firm patent propensities. In addition, endogeneity may also be caused by simultaneity because both import competition and R&D may be affected by a firm's patent behavior. We address it in several ways.

First, to alleviate potential endogeneity problems, all equations are estimated with lagged values of these explanatory variables. As a second approach, we also run instrumental variables (IV) regressions. 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., 2016; 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.

To capture the R&D variable, we follow the innovation literature based on the research initiated by Crépon, Duguet and Mairesse (1988) (CDM). The basis setup of the CDM model is a structural model that relates productivity to patents (output innovation), which depends on R&D (and other factors), which in turn is determined by the number of firms, industry, and other market characteristics. In equations (2) and (4) in section 5, R&D may be correlated with the error term if part of the R&D is attributed to unobserved firm-specific effects that can be corroborated with a firm's patenting activities. In addition, literature on endogenous models of innovation growth (e.g., Romer, 1990) postulates that a firm may invest in R&D if the expected pay-off is greater than the current investment costs. We therefore run a first stage regression using a Tobit model where we explain the log of R&D per employee as a function of the lagged log of employment, a dummy on past patent applications, the lagged log of competition, year dummies and unobserved heterogeneity. Unobserved heterogeneity is captured by the Wooldridge approach, defined earlier in the paper, when the averages of the continuously distributed explanatory variables are added. Following the empirical literature on CDM models, we then use the predicted R&D as an explanatory variable in the patent equation.

Overall the results in terms of the effect of R&D and import competition on patents, using the instrumental approach, are only a little affected. That is, the effects of R&D on patenting and import competition retain their sign and their significance. Using the full specification, our results show that the coefficient on the effect of the R&D coefficient on patenting equals 0.37 and is statistically significant in determining whether or not patents are positive, while we find a positive and significant impact on the level of patenting with a coefficient of 0.77. Similarly, the negative effect of import competition on both the probability and the level of patenting remains confirmed. The coefficients of import competition are -3.07 and -3.71 respectively. The coefficients of import competition on citations (type 1 and type 2) are very similar to the ones presented in table 5.2.1, except that we also find a significant negative effect on the citation2 probability with a coefficient of -1.71. We note that the validity of the instruments is tested using the Sargan test.

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.

Our research measured innovation at the firm level by counting the number of patent applications and the quality of those patent applications by the numbers of citations. Our results show that higher import competition in the Netherlands has a negative impact on the probability that a firm applies for a European patent and a negative impact on the number of patent applications as well. But it has no influence on the quality of the patents; with more import competition the number of citations does not increase or decrease significantly. These results unmask a striking heterogeneous response across firms of different innovation activities suggesting that more quality-driven innovative firms puts 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.

Whereas most studies only consider import competition from China and other emerging markets, we also take high developed countries into concern. We find that import competition from countries who were member of the EU before 2004 has a negative impact on the number of patents, whereas there is no statistically significant influence from newer EU member states, China or the group of countries in the rest of the world. The literature mostly focusses on import competition from emerging markets, usually low wage or middle wage countries. It is less common to consider import competition from high wage countries, such as the members of the European Union. 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 analysis can only distinguish industries and products, but not quality. It might come as a surprise that the rise of imports from China does not have an 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 labour (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 time period 2000-2010 that we study in this paper.

The data about import competition was compiled especially for this article. However, it could be used in many different settings. For example, to study the relation between import competition and employment (Smits, Vancauteren and Weyns, 2018), import competition and crowding out of local enterprises, import competition and wages.

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Appendix

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

A2. high, low and middle wage countries (World Bank classification)

High wage countries

American Virgin Islands
Andorra
Anguilla
Aruba
Australia
Australian Oceania
Austria
Bahamas
Bahrain
Barbados
Belgium
Bermuda
Bouvet Island
British Indian Ocean Territory
British Virgin Islands
Brunei
Canada
Cayman Islands
Ceuta
Christmas Island
Cocos Islands
Cook Islands
Countries not specified for reasons, EU
Countries not specified, EU
Croatia
Cyprus
Czech Republic
Denmark
Equatorial Guinea
Estonia
Falkland Islands
Faroe Islands
Finland
France
French Polynesia
French Southern Territories
Germany
Gibraltar
Greece
Greenland
Guam
Heard Island and McDonald Islands
Hong Kong
Hungary
Iceland
Ireland
Israel
Italy
Japan
Kuwait
Liechtenstein
Luxembourg
Macao
Malta
Melilla
Netherlands Antilles (until 2013)
New Caledonia
New Zealand
Niue
Norfolk Island
Northern Mariana Islands
Norway
Océanie américaine
Océanie néo-zélandaise
Oman
Pitcairn
Poland
Portugal
Qatar
Régions Polaires
San Marino
Saudi Arabia
Singapore
Slovakia
Slovenia
South Georgia and South Sandwich Islands
South Korea
Spain
St Pierre and Miquelon
Stores and provisions, EU
Sweden
Switzerland
Taiwan
Tokelau
Trinidad and Tobago
Turks and Caicos Islands
United Arab Emirates
United Kingdom
United States
United States Minor Outlying Islands
Vatican City
Wallis and Futuna

Low wage countries

Afghanistan
Bangladesh
Benin
Burkina Faso
Burundi
Cambodia
Central African Republic
Chad
Comoros
Gambia
Guinea
Guinea-Bissau
Haiti
Kenya
Kyrgyz
Liberia
Madagascar
Malawi
Nepal
Niger
North Korea
Rwanda
Sierra Leone
Somalia
Tajikistan
Tanzania
Togo

Congo (Democratic Republic)	Mali	Uganda
Eritrea	Mozambique	Zimbabwe
Ethiopia	Myanmar	

Middle wage countries

Albania	Indonesia	Peru
Algeria	Iran	Philippines
American Samoa	Iraq	Romania
Angola	Ivory Coast	Russia
Antigua and Barbuda	Jamaica	Saint Helena, Ascension, Tristan da Cunha
Argentina	Jordan	Saint Lucia
Armenia	Kazakhstan	Samoa
Azerbaijan	Kiribati	Sao Tome and Principe
Belarus	Kosovo	Senegal
Belize	Laos	Serbia
Bhutan	Latvia	Serbia and Montenegro
Bolivia	Lebanon	Seychelles
Bosnia and Herzegovina	Lesotho	Solomon Islands
Botswana	Libya	South Africa
Brazil	Lithuania	Sri Lanka
Bulgaria	Macedonia	St Kitts and Nevis
Cameroon	Malaysia	St Vincent and the Grenadines
Cape Verde	Maldives	Sudan
Chile	Marshall Islands	Suriname
China	Mauritania	Swaziland
Colombia	Mauritius	Syria
Congo	Mayotte (until 2014)	Thailand
Costa Rica	Mexico	Timor-Leste
Cuba	Micronesia	Tonga
Djibouti	Moldova	Tunisia
Dominica	Mongolia	Turkey
Dominican Republic	Montenegro	Turkmenistan
Ecuador	Montserrat	Tuvalu
Egypt	Morocco	Ukraine
El Salvador	Namibia	Uruguay
Fiji	Nauru	Uzbekistan
Gabon	Nicaragua	Vanuatu
Georgia	Nigeria	Venezuela
Ghana	Pakistan	Viet-Nam
Grenada	Palau	West Bank and Gaza
Guatemala	Panama	Yemen
Guyana	Papua New Guinea	Zambia
Honduras	Paraguay	
India		

A3. Estimating indirect import competition

Murray (2017) proposes to estimate the indirect effects using an input-output approach. We follow his approach and adapt his description for the specific Dutch case. We use the Dutch input-output tables for the time period 2000-2010 and aggregate the 128 industries to 79 industries (mainly on 2 digit NACE codes).
Let aij be the share of inputs that industry i purchases from industry j in total inputs (which is equal to total output). Then the first-order downstream import exposure of industry i is given by

$IE_i^D = \sum_j a_{ij} IE_j$

where IE_i is import exposure of industry j. IE_i^D can be interpreted as a weighted average of the import exposure of suppliers of industry i, where the shares of each supplier in total inputs (the a_{ij}) are the weights.
Similarly, let b_{ij} be the share of output of industry i that is purchased by industry j.

Then the first-order upstream import exposure of industry i is given by

$IE_i^U = \sum_j b_{ij} IE_j$

We now proceed to estimate total upstream and downstream effects, not only the first-order effects. Set IE as the column vector with as entries the total import exposure in industry j if it is one of our manufacturing industries under consideration and set it to zero if it is not. Set I as the identity matrix of size 79. Then the total upstream import exposure and total downstream import exposure are respectively defined as

$$IE^D = (I - A)^{-1} IE = L * IE$$

And

$$IE^U = (I - B)^{-1} IE$$

respectively, where A is the matrix with entries a_{ij}, B is the matrix with entries b_{ij} and L=$(I - A)^{-1}$ is the Leontief inverse that is commonly used in input-output analysis. Instead of IE, exposure to imports from all countries in the world, one can of course consider exposure to imports from a group of countries or a single country as well.

Explanation of symbols

Empty cell	Figure not applicable
.	Figure is unknown, insufficiently reliable or confidential
*	Provisional figure
**	Revised provisional figure
2018–2019	2019 to 2019 inclusive
2018/2019	Average for 2018 to 2019 inclusive
2018/’19	Crop year, financial year, school year, etc., beginning in 2019 and ending in 2019
2016/’17–2018/’19	Crop year, financial year, etc., 2016/’17 to 2018/’19 inclusive

Due to rounding, some totals may not correspond to the sum of the separate figures.

Colophon

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