Import competition and innovation: Evidence for the Netherlands

Mark Vancauteren, Ahmed Boutorat en Oscar Lemmers

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De wereld veranderde de afgelopen decennia in snel tempo; Oost-Europa opende zich, China trad toe tot de WTO, deze en andere landen die eerst een relatief kleine rol speelden in de wereldhandel zijn nu concurrenten van de traditionele industrielanden. In de literatuur is gekeken naar allerlei gevolgen van deze toegenomen importconcurrentie; onder andere op werkgelegenheid, huizenprijzen in regio's met veel concurrentie tot zelfs de huwelijkskansen van mannen werkzaam in bedrijfstakken met veel buitenlandse concurrentie. Er zijn echter sterk verschillende uitkomsten, afhankelijk van het land/de regio die bekeken wordt. In dit artikel kijken we daarom naar de gevolgen van de toegenomen importconcurrentie op innovatie in Nederland.

Raken bedrijven ontmoedigt omdat ze de concurrentie uit het buitenland niet meer de baas kunnen en innoveren ze minder? Of schakelen ze juist een tandje bij om de concurrentie voor te blijven en innoveren ze juist meer? We meten innovatie hierbij met het aantal aangevraagde patenten van bedrijven en meten de kwaliteit van die patenten met het aantal citaties door andere patenten. We beperken ons vanwege databeschikbaarheid tot de industrie in de periode 2000-2010.

Onze econometrische analyse laat zien dat import competitie in Nederland een negatieve invloed heeft op de kans dat een bedrijf een extra Europees patent aanvraagt, en op het aantal aangevraagde patenten door een bedrijf. Maar het heeft geen invloed op de kwaliteit van de patenten; als er meer importconcurrentie is dan worden de patenten die aangevraagd worden niet meer of minder geciteerd. Importconcurrentie uit de landen die vóór 2004 al lid waren van de EU heeft een negatieve invloed op het aantal aangevraagde patenten, maar importconcurrentie uit "nieuwe" EU-lidstaten, China en andere niet-EU-landen niet.

Andere resultaten uit onze studie zijn dat meer R&D uitgaven bij een bedrijf en meer verschillende soorten bedrijfsactiviteiten gepaard gaan met meer patenten en vaker geciteerde patenten. De grootte van het bedrijf (aantal werknemers) heeft een wisselend effect, terwijl het in buitenlandse handen zijn gepaard gaat met minder patentaanvragen en een lagere kans om geciteerd te worden.

De resultaten voor patenten die alleen in Nederland geldig zijn, zijn over het algemeen overeenkomstig; importconcurrentie en in buitenlands eigendom zijn leidt tot lagere kans om een extra patent aan te vragen en tot minder patentaanvragen. Meer R&D uitgaven gaan juist samen met grotere kans op nieuwe patenten en meer patenten. En meer verschillende activiteiten in de onderneming leiden tot een grotere kans op nieuwe patentaanvragen, maar niet tot meer aanvragen. In tegenstelling tot de Europese patenten geldt bij de Nederlandse patenten dat hoe groter het bedrijf, hoe groter de kans op extra patenten en meer patenten.

Vervolgonderzoek kan naast de rol van import competitie door import van goederen ook de rol van import van diensten bekijken. Daarnaast kan het ook de hele waardeketen meenemen in plaats van alleen de bedrijfstak die importeert. Want als een bedrijfstak positief of negatief geraakt wordt door importconcurrentie, dan kunnen ook de toeleveranciers en de afnemers van deze bedrijfstak de positieve of negatieve gevolgen ondervinden.

Import competition and innovation: Evidence for the Netherlands

1. Introduction

Innovation makes firms more competitive. 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 from more reliance on external financing which might hamper innovation. On the other hand, it might also push them to keep innovating to remain competitive (Bloom et al., 2016). The important economic question in this paper is as follows: Does import competition promote innovation and thus productivity and growth, or does it discourage it? The empirical evidence of recent papers remains mixed. While some papers find positive effects of competition (e.g., Bloom et al., 2013 and 2016; Li and Zhou, 2017; Chakravorty et al., 2017), others find almost no, mixed, or even negative effects (Autor et al., 2016; Hombert and Matray, 2015).

This report focuses on import competition from the perspective of the Netherlands. We contribute to the literature in several ways. First, 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, 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. Our data allows us to distinguish import competition from various income-level countries which could also have varying impact on innovation (Li and Zhou, 2015). 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 (2015) 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.

Second, we employ data not only about patent applications 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. 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.[1] With patent applications, the time of filing or applying for a patent coincides very closely with the time that innovative activities take place within a firm (OECD, 2009). Patents represent the output of the innovation process (for example, due to R&D), measuring a technological invention by which the technological knowledge to other firms is disclosed. We connect the patent information to more detailed innovation characteristics. The patent data also incorporates information on patent applications that are only applied for at the Netherlands Patent Office (Octrooicentrum Nederland) and are not double counted as EPO patents. This allows us to control for capturing additional firm heterogeneity in terms of patent activities related to firm size and economic international activity. In addition, we also incorporate information about forward patent citations. We consider two citation measures. 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 (Nagaoka et al., 2010). 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 the patent database PATSTAT (namely, European Patent Office (EPO), US Patent and Trademark Office (USPTO), Japanese Patent Office (JPO)), for all EPO patent applications (counts) for each sample firm. The second type of forward citations differs from the previous definition in that a so called patent family data is used to construct the number of citations. A patent family refers to the set of patent applications across countries that

[1] 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.

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 the 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 of 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.[2]

Thirdly, we contribute to the literature by considering the enterprise group and then 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.

Fourth, we use data from National Accounts that is integrated at the industry level instead of using data from different sources about turnover, imports and exports that is not always well-aligned. National Accounts harmonizes definitions, concepts and classifications in order to make comparable statements through time, whereas the trade and turnover statistics do not always do that. Furthermore, in the Netherlands a large part of imports and exports consists of re-exports (Statistics Netherlands, 2016), but the trade statistics have no accurate estimates of import for re-exports yet.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the literature. Section 3 provides some industry level evidence for patents and import competition, whereas section 4 describes the data set. Section 5 presents the empirical model and in Section 6 we present the estimation results. Finally, Section 7 concludes.

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

2. Background

Innovation studies analyzing the relationship between competition and innovation predict three types of relationship between competition and product innovation: a negative relationship, a positive relationship and a bell-curve or inverted U-relationship.

There is theory (e.g., Arrow, 1962) that supports a positive relationship; it predicts that firms innovate to escape competition: firms will innovate if the profits from the new innovation exceed their current profits by more than the cost of the innovation. In other words, the incentives of firms to innovate depend not only on the profits from the new innovation (post-innovation rents) but also on the difference between this and the profits before the innovation (pre-innovation rents), offset by the costs of innovation. It follows that if the number of firms are low, and those firms enjoy high pre-innovation rents, then the incentives to innovate are lower.

Theory (e.g., Schumpeter, 1934) that predicts that innovation should decline with competition is based on the assumption that with more firms entering the market, the profit margins get smaller and smaller, leaving less space for innovating. This is called the Schumpeterian effect. The implication of this view is that an increase in the number of competitors would destroy rather than enhance the incentives to innovate.

Aghion et al. (2005) present a theory known as the inverted U or bell-shaped theory reconciling these two conflicting theories. According to this theory, the relationship between the level of competition and innovation is dependent on the initial level of competition. 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. However, those firms in the leveled market will have higher incentives to innovate. As a result, the market remains unleveled with a Schumpeterian effect on the laggard firm while the follower never innovates. Aghion et al. (2005) found empirical support to the inverted-U prediction with data on UK firms' patenting activity at the US patenting office. To conclude, this study confirms that the optimizing level of innovation lies in between that of pure monopoly and perfect competition.

2.1. International competition

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 parallel to the closed economy model, the expected impact of exposure to trade openness on the innovation incentives of domestic firms is subject to the same theoretical predictions from which no clear consensus can be made.

For local firms, import competition, for instance, as a response to trade liberalization, 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 '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 intrafirm allocation whereby import shocks might induce a reallocation of resources toward the more technologically advanced firms, indirectly boosting resource allocation to innovation activity.

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, 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.

2.2. Heterogeneous competition effects

Another important aspect concerns the heterogeneous impact of competition on innovation. The concept of heterogeneity draws upon specific elements of productivity maximization where the productivity effects of innovation may vary according to some lower and upper bounds. For instance, Farell (1957) develops the concept of the so called “technical inefficiency” which means that a firm that has a lower ability, or applies less effort to absorbing new technology, will produce less output than the one operating with the best available technical know-how. This matches the idea of technical frontier found in growth theory. Within this context, the distance-to-frontier approach emphasizes the argument that the effectiveness of innovation is conditional to a firm's, industry's or country's distance to the technological frontier.[3]

Ding et al. (2016) distinguish the heterogeneous effects of import competition on firms' productivity according to the distance-to-frontier approach. The authors hypothesize that fiercer import competition augments productivity of those domestic firms which are close to the frontier so that they can cope with foreign competition. While on the contrary, firms further behind the frontier are less inclined to innovate due to limited resources and find it more difficult to deal with new competition. Using Chinese firm-level and international transaction data being linked to US industry data for the period 2000-2006, the authors 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.

Another important aspect related to heterogeneity is to 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 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.

Chen and Steinwender (2016) develop a partial equilibrium model, a heterogeneous firm model with endogenous productivity and heterogeneous preferences of managers. Their model predicts a distinctive pattern of heterogeneous productivity responses that depends not only on the type of manager but also on the firm's initial productivity draw. Consistent

[3] One of the main shortcomings of neoclassical growth theory is that technology is exogenously determined and is left un-modeled. Instead an important contribution of endogenous growth theory, originated by Romer (1990), is the recognition that technological progress (captured by the search for new ideas by researchers) occurs as profit-maximizing behavior. In this way, improvements in technology and economic growth are endogenous outcomes of the model.

with their empirical findings using Spanish firm-level data, the model mechanism considers that at low initial productivity levels, managers who care most about private benefits and cost relative to firm profits (which is inherent for family firms), increase their managerial efforts to offset import competition to ensure survival. Whereas at initial high productive levels these managers reduce their efforts as they are discouraged by more import competition and the corresponding shrinking market share. The evidence in this paper suggests that competition can incentivize unproductive family firms to improve productivity.

2.3. Economics of patents

Patent data, used to establish the link between import competition and innovation, has some distinct features. The innovation literature considers several indicators for innovative activities such as the new products for the market, R&D or the use of patent applications. It is noted that firms are more likely to patent as this may be considered as a major determinant that augments firm performance (Nagaoka et al., 2010). 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[4], it is not a surprise that competitive effects linked to R&D follow a same (positive or negative) pattern.

3. Industry level background information on patents and import competition

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

<Insert figure 3.1>

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.

<Insert table 3.2>

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[4] 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.

Table 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.

<Insert table 3.3>

The differences across industries are also very apparent when considering the import competition at industry level. Table 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, no industry has faced a large incline in import exposure over the years.

4. Data

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. More recent data was not available at the time of writing the paper. 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.

4.1. 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

[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 this 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.

(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 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 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 B1.

Summary statistics of our key variables (in the transformation used in the analysis) are shown in table A1. The statistics are based on the total sample of firms from the period 2000-2010. The unweighted average firm in our sample applies approximately for 1.7

[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.

patents a year, with an average forward citation count of 1.5 and 2, spends on average $e^{7.08}$ * 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 $e^{2.790}$ = 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 A2 provides similar summary statistics, now by industry.

4.2. 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 that measure 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 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.

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

$$Import\ competition\ from\ China\ in\ industry\ j\ in\ year\ t = \frac{M_{j,t}^{China} - M_{j,t-1}^{China}}{Y_j + M_j - X_j}$$

Here M_j^{China} are the imports from China of products of industry *j,* Y_j are the shipments 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 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. 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].
- $Y_{j,}$ total production of industry *j,* is extracted from the same database of national accounts

[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 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.

- Subsequently, we obtain from this database the value of imports and exports of each good. We exclude imports for re-exports and 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; 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.

As has been explained above, 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:

[10] Example: say trade statistics has 100 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.

- About half of Dutch trade in goods considers of re-exports, 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, whereas 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.

5. Empirical Implementation; the models

We estimate a similar 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.

[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.

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

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

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

$$ln\lambda_{it} = \alpha_{1i} + \delta_1 IC_{i,t-1} + \boldsymbol{\beta}_1' \boldsymbol{X_{1it}}, \tag{2}$$

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 $\boldsymbol{X_{it}}$ represents firm i characteristics. Turning to the coefficients, α_{1i} is a time-invariant unobserved firm-effect, and δ_1, $\boldsymbol{\beta_1}$ 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 $\boldsymbol{X_{1it}}$). 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,

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

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

[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.

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 p_{it} as,

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

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). [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,

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

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

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).

6. Empirical results

6.1. Baseline results

We now consider the estimates of the patent equation discussed in section 5. Table 6.1.1 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. As a consequence, we only report the outcomes based on the Negative Binomial distribution. 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 with random effects. 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).

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 – 1.792 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 1.792 percentage points. The coefficient of -2.847 in the column next to it, at "Patents", indicates that a one percentage point increase in import competition leads to a firm applying for 2.847 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. 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.

<Insert table 6.1.1>

6.2. 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 6.1.1, 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 6.2.1. 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. In the very last column, we evaluate the impact of import competition on the number of forward citations when we separate firms into a subsample that only include firms with patent citations that are strictly positive, using a Negative Binomial estimation. Again we find that import competition has no impact on the quality of innovation as measured by the number of forward citations of patents families. This result reveals that there is no heterogeneous impact in terms of innovation upgrading; there is no difference between firms that apply for patents often or those who rarely do so. 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 some evidence that the larger the enterprise group, 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.

<Insert table 6.2.1>

6.3. 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 6.3.1 indicate that 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 (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.

<Insert table 6.3.1>

6.4. 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 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.[14] The results summarizing the impact of import competition on the number of local patent applications are listed in table 6.4.1. In the first two columns, we use the model for the number of patent applications with random effects and add an interaction between import competition and a binary indicator that is equal to one if firm has only applied for patent protection on the Dutch market.

The nature of the results is comparable to that of those in table 6.1.1, 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. However, the size of the coefficients for import competition is much larger in table 6.4.1 than in table 6.1.1. For example, an increase of 1 percentage point in import competition for a given enterprise

[14] We refer to Kuipers (2010) and Vos (2017) for a detailed firm-patent descriptive analysis.

group will on average lead to a decrease in European patent applications of 3, but a decrease in Dutch patent applications of 6.

<Insert table 6.4.1>

6.5. 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 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 -6.07 and -6.71 respectively. The coefficients of import competition on citations (type 1 and type 2) are very similar to the ones presented in table 6.2.1, except that we also find a significant negative effect on the citation2 probability with a coefficient of -4.71. We note that the validity of the instruments is tested using the Sargan test.

7. Conclusion

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. 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.

Other results from our studies are that more R&D expenditures and more different activities at firm level lead to more patents and more cited patents. The size of a firm has mixed effects, whereas foreign enterprises have less patents and less cited patents.

A novelty in our study is that we use data from National Accounts about imports, exports and turnover at the industry level instead of using data from enterprise statistics. 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, changes of classifications and so on.

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, import competition and crowding out of local enterprises, import competition and wages and so on. Further research could extend import competition by adding trade in services as well and by considering the whole value chain. Murray (2017) gives examples showing that if an industry is affected by import competition, its suppliers and its clients might be affected indirectly as well.

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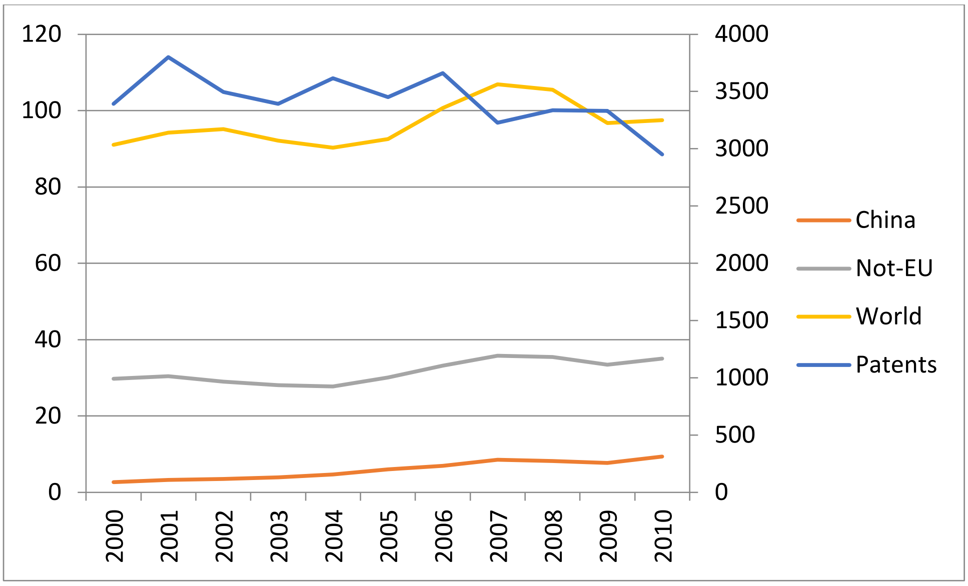
Appendix A: Results

Figure 3.1: Dutch patent applications to the EPO and competing imports (constant prices) in the manufacturing sector



Source: Eurostat.

Table 3.2: Patent applications to the EPO in the manufacturing sector

Industry (ISIC Rev. 4)	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
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-metallic 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, electrical 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, transportation (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.

Table 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-metallic 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, electrical 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, other transportation (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.

Competing imports divided by total supply for domestic market, both in constant prices, expressed in percentages

Table A1: Sample Means and Standard Deviations, 2000-2010

Summary statistics of the overall sample consisting of 2294 panel firm-year observations. Number of firms is 1472.

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	7.080	(3.141)	5.771	6.905	8.389
Foreign Y/N 1/0	0.410	(0.492)	0	0	1
Number of activities	3.220	(3.173)	1	2	4
Number of firms	5.40	(5.597)	1	3	6
Log Competition	2.790	(0.665)	1.210	2.202	2.822

Table A2: Summary statistics (Total sample; analysis sample is a subset)

Industry	NFirm	AR&D	AEmpl	APat	ACit1	ACit2	AImpC
Food (10-12)	388	9184.62	274.58	1.18	10.12	55.37	0.87
Textiles, clothing (13-15)	65	1340.99	152.02	0.26	1.266	4.30	-0.34
Wood, paper, printing (16-18)	192	2825.04	321.90	0.12	1.57	5.86	-0.34
Chemicals, pharmaceuticals (19-21)	198	23203.56	496.82	4.58	10.01	8.28	0.75
Plastics, non-metallic minerals (22-23)	292	1063.65	140.90	0.22	2.62	4.42	0.76
Basic, fabricated metals (24-25)	464	2659.88	160.27	0.24	2.81	4.49	0.44
Computers, electrical equipment (26-27)	176	83118.43	511.90	20.39	25.83	650.41	-0.29
Machinery, equipment n.e.c. (28)	684	9970.97	129.60	0.54	7.35	20.21	-1.01
Motor vehicles, other transportation (29-30)	160	9659.69	257.23	0.33	3.59	6.65	-0.11
Furniture, n.e.c. & recycling (31-33)	393	6689.40	138.21	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 6.1.1: Patents and import competition

Note: 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.

Variables	I Logit (Y/N)	Patents	II Logit (Y/N)	Patents	III Logit (Y/N)	Patents
Lag (Import competition)	-1.749* (1.027)	-2.962** (1.175)	-1.614 (1.021)	-2.664** (1.241)	-1.792* (1.056)	-2.847** (1.190)
Lag (log (1+R&D per employee))	0.227*** (0.028)	0.297*** (0.031)	0.217*** (0.028)	0.254*** (0.028)	0.219*** (0.029)	0.256*** (0.029)
Log(Employment)	0.279*** (0.045)	0.600*** (0.062)	0.194 (0.138)	-0.082 (0.155)	0.161 (0.149)	-0.227 (0.169)
Log(Competition)					0.246 (0.188)	0.121 (0.129)
# Activities					0.165*** (0.035)	0.155*** (0.032)
# Firms					-0.039*** (0.011)	-0.032*** (0.009)
Foreign Y/N (1/0)					-0.255** (0.102)	-0.399*** (0.120)
Intercept	-3.740*** (0.268)	-5.312*** (0.363)	-3.717*** (0.266)	-5.229*** (0.316)	-4.591*** (0.268)	-5.347*** (0.501)
alpha		3.964*** (0.371)		3.521*** (0.254)		3.266*** (0.260)
Random effects Year dummies	NO YES		YES YES		YES YES	
Log-likelihood	-5252.186		-5266.037		-4530.234	

Table 6.2.1: Citations and import competition

Note: 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.

Variables	I Logit (Y/N)	Citations1	II Logit (Y/N)	Citations2	Citation2 (>0)
Lag (Import competition)	-3.280** (1.417)	-0.251 (1.179)	-0.605 (1.175)	0.003 (1.990)	0.241 (1.870)
Lag (log (1+R&D per employee))	0.184*** (0.035)	0.214*** (0.035)	0.242*** (0.033)	0.256*** (0.033)	0.191*** (0.023)
Log(Employment)	-0.154 (0.169)	-0.378* (0.225)	0.121 (0.183)	-0.265 (0.177)	-0.401** (0.195)
Log(Competition)	0.010 (0.163)	0.055 (0.232)	0.234* (0.138)	0.193 (0.215)	-0.290 (0.270)
# Activities	0.129*** (0.038)	0.156*** (0.047)	0.159*** (0.036)	0.172*** (0.042)	0.040 (0.030)
# Firms	-0.035*** (0.012)	-0.036** (0.014)	-0.043*** (0.012)	-0.031*** (0.012)	-0.008 (0.008)
Foreign Y/N (1/0)	-0.449*** (0.132)	-0.254 (0.210)	-0.321*** (0.113)	0.003 (0.199)	-0.130 (0.159)
Intercept	-5.131*** (0.567)	-3.795*** (0.751)	-4.899*** (0.503)	-2.958*** (0.737)	-1.450*** (0.300)
alpha		11.920*** (0.951)		9.460*** (0.603)	1.700*** (0.090)
Random effects	YES		YES		YES
Year dummies	YES		YES		YES
Log-likelihood	-3171.541		-4677.013		-1300.011

Table 6.3.1: Patents and import competition, by destination

Note: 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.

Lagged import competition by destination	I Logit (Y/N)	Patents	II Logit (Y/N)	Citations 2	III Logit	IV Patents
China	-1.275 (8.689)	-2.131 (9.123)	0.378 (10.439)	-10.911 (9.551)	-1.331 (8.777)	-1.607 (9.027)
Rest of World	0.911 (2.518)	-0.531 (2.590)	2.859 (2.849)	3.320 (3.911)	0.943 (2.501)	-0.641 (2.532)
EU total	-3.209** (1.644)	-4.161** (1.655)	-2.550 (1.794)	-1.533 (3.001)		
EU New					-9.187 (14.356)	17.016 (18.990)
EU Old					-2.910* (1.779)	-5.291*** (1.781)

Additional notes: not shown in the table are the estimates for the variables as in 6.1.1 and 6.2.1, 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.

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.

Table 6.4.1: Local patents and import competition

Note: 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.

Variables	I Logit (Y/N)	Dutch Patents	II Logit (Y/N)	Dutch Patents
Lag (Import competition)	-4.554*** (1.193)	-6.131*** (1.283)	-2.350** (1.077)	-3.628*** (1.180)
Lag (Import competition*NL_only (1/0))			-3.533*** (1.150)	-1.627 (1.059)
Lag (log (1+R&D per employee))	0.056** (0.022)	0.119*** (0.022)	0.225*** (0.029)	0.209*** (0.020)
Log(Employment)	0.348* (0.193)	0.737*** (0.264)	0.344* (0.192)	0.726*** (0.261)
Log(Competition)	0.091 (0.135)	0.193 (0.136)	0.090 (0.135)	0.190 (0.136)
# Activities	0.107*** (0.035)	0.026 (0.037)	0.107*** (0.035)	0.026 (0.037)
# Firms	-0.031*** (0.012)	-0.02* (0.012)	-0.031*** (0.010)	-0.020* (0.012)
Foreign Y/N (1/0)	-0.729*** (0.115)	-0.983*** (0.126)	-0.731** (0.114)	-0.983*** (0.126)
Intercept	-3.083*** (0.466)	-4.593*** (0.673)	-3.909*** (0.301)	-4.580*** (0.473)
alpha		3.764 (0.283)		3.758*** (0.283)
Random effects Year dummies	YES YES		YES YES	
Log-likelihood	-3128.894		-3200.125	

Appendix B

Table B1. 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