An Empirical Assessment of Defensive Innovation to Chinese Import Competition in Japan

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Abstract:
This paper empirically examines the defensive innovation hypothesis that firms which have been more exposed to low wage country import competition intensively undertake more innovative activity, using the high quality Japanese firm-level panel dataset over the period 1994-2005. The novel feature of the analysis is to relate firm-level variations of the patent usage to import competition. The preliminary results suggest that intensified import competition from China has resulted in more innovative activity of Japanese firms, consistent with the finding of European firms in Bloom et al. (2015). Moreover, such competition has also led to both an increase in patents that are used as well as non-used. This finding remains robust to instrumenting Chinese import competitions, the inclusion of other firm-level controls, and measures of import competition from other high and middle income countries.

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1. Introduction

This paper examines the 'defensive innovation' hypothesis first discussed in Wood (1994) and subsequently formalised in Thoenig and Verdier (2003): As the response to import competition from low wage countries, firms in developed countries would respond by upgrading their innovative activities, leading to 'defensive skill-biased innovation'.

In a more broad context, the effect of competition on the rate of innovation has been one of the most studied areas in industrial organisation (the empirical finding in Aghion et al. (2005) discover the non-monotonic relationship innovation and competition, and many other studies followed). In the most relevant study to our paper, Bloom et al. (2015) find that a large sample of European firms increases a wide range of their innovative activities (patenting, research and development (R&D) expenditures, computer use, and the TFP growth) driven by intensified competition from China. This is found within-firm.[1]

Building on the foundation of the above studies, this paper examines the causal effect of the intensified Chinese import competition on innovate activities of a panel of Japanese firms for the period 1994-2005. We focus on the patent usage data as an indicator of innovative outputs. Unlike other studies using the patent statistics, this study adds to the literature by exploring the strategic patent usage as responses to import competition from a low wage country (China). It is generally acknowledged patent statistics are meaningful proxies for firm-level innovation, but it has been known for a long time that firm-level patenting reflect much more than as an indicator of knowledge capital output (Griliches, 1981; Nagaoka et al, 2010). The well-known inventor surveys have revealed (the RIETI-Georgia Tech on US-Japan, the Carnegie Melon, Yale) that many of the patents are not used to introduce new products in the market, instead they are used as the effective strategic instruments in order to 'block' other competitors from innovating or they work as the prevention mechanism for imitation (Boldrin and Levine, 2013 presenting a nice case of Microsoft – an incumbent with the stock of patents blocking Google in the smartphone market).

[1] Amiti and Khandelwal (2013) find that increased import competition (measured by a decline in tariff) spurs a country's export quality (measured by the market share) in the US market.

Studying innovative firms’ responses to Chinese import competition provides an interesting and excellent testing ground for the following reasons. First, over the past decades China has emerged as a pivotal assembly export country of high-tech products (mainly, the electronics goods), importing parts and components from other advanced countries and exporting final products (including a famous case of ‘i-phone’). Accordingly, China’s export bundle has dramatically changed from labour-intensive goods to high-tech products, exerting considerable competitive pressures on firms in developed countries. Second, many of Chinese exports compete at lower cost margins of high-tech products. For instance, a study by Schott (2003) found that China’s export similarity index has become closer to that of OECD countries, but the unit prices of Chinese exports have been consistently lower than OECD countries.

The preliminary finding suggests that Chinese import competition leads Japanese firms to expand their innovative activities in terms of growth of patents owned by firms. This is partly driven by an increase in unused patents by firms.

The organization of this paper is as follows. The next section briefly summarise theory, followed by an overview of Chinese export performance in world trade in Section3. Then, Section 4 discusses the dataset, followed by the empirical approach and a discussion of the preliminary findings in Section 5. Section 6 concludes the paper.

2. A Summary of Theory

There are a large number of theories of how the competitive pressures (including triggered by trade liberalisation) could affect the rate of technical changes in countries.[2]

One strand of the literature takes an approach of industrial organisation pertaining import competition and how incumbent firms respond to such competition (Aghion; Amit and Kandelwal). Other studies extend the line of research in the tradition of Helpman and Coe.

[2] More broadly defined as the market structure and the innovation incentives track back as far as the time of Schumpeter.

Lowering import barriers in general increases competition and competitive intensity can increase innovation. However, the effects of competition on innovation are theoretically ambiguous in general. Aghion et al. (2005) and his associates) show that increasing competition (here in a broad term, not necessarily from trade liberalisation) reduces innovation if the firm is far from the technology frontier because of a 'discouragement' effect. This is shown in the highly stylised industrial organisation model (Bertrand). Any lagging firms far from the frontier know that they cannot survive from increased competition, leading to a discourage effect on any resources used on innovations. In contrast, firms closer to the technological frontiers have more incentives to innovate when threaten by competition (or any policy driving it), because they can 'escape' from the competition (the escape-entry effect). Leading incumbents can avoid any losses that would have resulted without innovation. The core insight generates the famous 'inverted U-shaped' relationship between competition and innovation.

Bloom, Romer and Van Reenen (2010) develop a more stylized model of trade-induced innovation – 'trapped' factor model. The basic assumption is that firms can allocate a factor of production either to produce old goods or innovate and produce new goods. China can produce old goods, but cannot (as easily) innovate and produce new goods. At the beginning of the period there are factors of production employed in Northern firms making old goods (protected by trade barriers). These factors are "trapped" in the sense that there is some human or fixed capital that is specific to the old good that is lost for a period if the firm chooses to reallocate the factor from producing the old good to innovating a new good. The magnitude of the firm-specific capital determines the opportunity cost of innovation and if it is sufficiently high the firm optimally chooses not to innovate. When import barriers are lowered, Chinese exports increase and the profitability of making old goods falls. Therefore, the opportunity cost of using the trapped factors for innovating (rather than producing the old good) falls, making innovation more attractive.

A fall in trade costs with China means that producers of goods that can use Chinese intermediate inputs will benefit. For example, firms may slice up the production process and offshore the low-TFP tasks to China (see for example Grossman and Rossi- Hansberg, 2008). This will have a compositional effect if the remaining activities in the home country are more technologically advanced. To investigate this mechanism we need to investigate offshoring activities to China (*not done yet*).

3. The Rise of China in World Trade

Figure 1-A depicts the rise of China in world exports for the period 1990-2011. In 1990 China's exports accounted for the tiny share (around 3%) in world exports. Since then, China's share has gradually increased. In particular, China's export growth took off since around the early 2000s. In the second half of 2000s, China has achieved a formidable export expansion by overtaking Germany for the position of the world's largest exporter, accounting for above 10% of world exports. China's export share has been growing without any disruptions, while the world shares of Japan, the USA and Germany have not grown during the same period. At the same time, China has also been growing to become an important country in the world important market (**Figure 1-B**). While the USA still accounts for the bulk of world imports (around 15-20% in world imports), its share has gradually been declining since 2000. Instead, China's share has been steadily increasing from the lower base accounting for close to 10% in 2011.

Figure 1 here

With the rise of China in world trade, its specialisation has dramatically changed as well. **Figure 2** depicts the share of relatively more capital and technology-intensive products of electrical machinery and household electric appliances as compared to more labour-intensive products of textiles and toys. There has been a notable shift of comparative advantages from more labour-intensive products towards more capital and technology-intensive products. In 1992 textiles and toys account for around 45% in China's total exports. However, its share continuously declined and dropped to close to 20% in 2011. On the other hand, the export share of electrical machinery and household appliances doubled the share from less than 15% in 1992 to 30% in 2011. In this product category, the export composition is highly concentrated in 'Information Communication Technology' (ICT) products. Other important product categories include office machines, and telecommunication sound equipment (including mobile phones).

Based on the income weighted export bundle of Chinese goods (eg, Rodrik 2006), some commentators argue that this is a sign that technological capability of China is rapidly converging to the technological frontier of advanced OECD countries ladder and is now directly competing with them in the export market. However, this should be interpreted cautiously. Once allowing for intra-product specialisation it is known that China's export specialisation still largely rests on the labour-intensive assembly stage rather than specialisation in technological content (Athukorala 2009). In other words, China's comparative advantages still rests on labour-intensive segment in high-tech products, even though these products are exported from China (a final assembly country). This explains why Schott (2008) observes that the unit price of Chinese export bundles are at lower end of the price range, as compared to those of OECD countries (the price competitiveness coming from China's lower labour costs). In sum, the bulk of Chinese exports are the mass-market commodities assembled with relatively low unit costs and imported high-tech parts and components from other industrial economies (notebook computers, mobile phones).

Figure 2 here

Chinese Import Competition in Japan

Table 1 sorts the top 8 industries by the degree of Chinese import competition and the bottom 8 in 1994 (the beginning of the estimation period).[3] In textile industry where Chinese firms are considered to have comparative advantages the degree of import competition was already felt strong in 1994 – within Japan's import in textile products, 49 per cent came from China. That share continued to increase reaching 77 per cent in 2005. More strikingly, the largest increase in the share of China in Japanese import is Office and service industry machines; it went up from 19 per cent in 1994 to 76 per cent in 2005. Correspondingly, in the all industries whereby China's share increased also led to a decline in the shares of Asian NIEs (Taiwan, Hong Kong, South Korea and Singapore) and the U.S. In the bottom 8 industries, an increase in China's share is palpable with strong growth in Electronic equipment and Semiconductor devices. Possibly production networks between Japan and China may explain an expansion in Chinese import in those high-tech industries.

[3] Year 1990 data is used in an experimental stage but the order import completion exposed industries are roughly the same to year 1994).

Table 1 here

4. Data and Variables

Firm-level Patent Data

Patent statistics have recently become widely available to researchers asn an indicator for innovative outputs because of a significant progress made in the data accessibility (US NBER patent, Japan Patent Office, PATSTAT). Patent statistics carry important invention related information such as bibliographic data (backward and forward citations, the technology fields, name of inventor, and usefulness). However, it has been well documented from the survey-based studies that not all patents are in-use ('sleeping'). In the case of Japan, it has been reported that around 60% of patents owed in the pharmaceuticals industry are not currently in use (Nagaoka et al. 2013)[4] . Rather, firms take out patents in order to provide the defensive blocking mechanism in the response to the technology competition.[5] For example, an important reason for such blocking patens might be to protect the market exclusively of own technology that is being commercialised. We, for the first time in the literature, empirically relate this unexploited nature of patent holdings to import competition from a low-wage country.

For this purpose, we extract the relevant data from Japanese firm-level surveys - the Basic Survey of Business Structure and Activity, conducted by the Ministry of Economy, Trade and Industry ('METI data').[6] In this project, we have access to the data covering the period 1994-2005.

The firm-level patent usage data is then merged with industry-level exposures to Chinese import competition, resulting in the unique dataset for the following aspects. First, it provides

[4] More generally, it is more common in the *discrete* technology industries. In this industry usually R&D takes as long as 10-15 years for new drugs to be introduced to the market. Hence, there are the substantial number of patents, still in the process of R&D and not used for drug in the market.

[5] It is important to note that those unused patents my just reflect the fact that firms currently does not have the internal assets to commercialise it or holding in searching for licensees.

[6] This survey is governed by the statistical law in Japan, hence failing to reply results in the fine. The survey sample is restricted to firms that have both more than 50 employees and capital of more than 30 million yen. It collects firms' accounting information (sales, employment, employment compensation, the number of establishments, R&D spending, exports, and imports). The industry classification is available at 3-digit level. But, for our purpose of analysing the impact of import competition, we restrict the sample to only manufacturing firms. All individual firms are assigned unique identifiers, making it possible to track operations of the same firms over time (the panel data).

a panel dataset of the patent usage related to the competitive pressures. The available surveys tend to report single-year responses, only depicting the static nature of patent usage.[7] The use of panel of firm-level data takes to the next step by offering the perspective of within-firm variation of the patent usage in response to import competition. Second, the data period is long enough to cover China's changing comparative advantage from more labour-intensive to more skill and technology intensive goods. Third, the added advantage of using the panel data is to allow firm-specific effects to be included because (unobserved) managerial skills (assuming time variant intra-firm elements) can be controlled in addition to industry and year fixed effects. Clearly, in a cross-sectional setup, this cannot be controlled for.

Based on firm-level information, we create the patent usage variables as follow (shown in Figure 3). In short, for each firm we have the count of patents owned (PAT), the count of those patents in use (USE) and no-use (NONUSE). Within PAT_USE, we have information for the count of patents based on internal inventions (DEV), and the count of patents which are licensed out (LICENSE). These variables form the dependent variables in a regression analysis below.[8]

Figure 3

It is equally important to note several limitations as well. First, the patent statistics in our data is a patent pool – all patents in which the firms have the ownership. The empirical work which use the patent statistics collected from the patent office normally cover those patents which are applied as well as being granted by the firm. In our data, all patents are presumably those granted (because the survey question asks how many patents a firm has ownership, rather than patents that being applied for or being granted). Since those patent applications can indicate firms' innovative efforts, our measure may underestimate them.

[7] Motohashi (2008) uses the data from the Survey of Intellectual Property Activities by the Japan Patent Office (JPO) conducted in year 2001 in order to classify the patents usage. It is found that some of patens are withheld by firms wishing to use (or license out) in the future. Or, they may be kept because a firm needs them for future licensing negotiations. This practice is common in the electronics industry where cross-licensing is more frequently use (Hall and Ziedonis, 2001).

[8]

Second, our patent data is simply the count. However, other studies employing the patent statistics usually weight the patent count to its (backward and forward) citations. Hence, it can control for the quality of patents. The higher quality (or sometimes more basic) inventions attract more forward citations than lower quality (sometimes, referred as 'patent thickness'). With no linked made between our patents owned by the firm in our data and the citation information, we are unable to account for this quality dimension.

Third, our data does not adjust for the depreciation rate for out-dated patents. It is more appropriate to adjust for the depreciation rate of patents, because some patents held by firms can become obsolete. However, with no identification of the grant (or application) date of each patent, the deprecation rate cannot be applied in our data. We therefore look at the growth rate of each patent usage (rather than a simply count), hoping to minimise the bias coming from the non-depreciation of the patents.

Japan Industry Productivity (JIP) Data

Industry level variables used in the regression analysis are mainly sourced from the Japan Industrial Productivity (JIP 2013) stored at the online database in the Research Institute of Economy, Trade and Industry (RIETI) in Japan.[9] The JIP dataset is organised at 3-digit industry level (52 manufacturing industries).

Chinese Import Competition

We use the value of imports originating from China (IM^{China}) as a share of total world imports (IM^{World}) as a measure of the exposure to Chinese import competition in given JIP industries (a subscript *j*) .

(1) $$CHM_j = \frac{\text{Chinese imports}_j}{\text{Imports}_j}$$

We also employ the conventional method of constructing Chinese import penetration by normalising Chinese import on domestic absorption (ie, domestic absorption=value added + imports – exports).[10]

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[9] http://www.rieti.go.jp/en/database/JIP2013/ See the Appendix for further details on JIP database.

[10] Value-added is defined as the difference between gross output and intermediate inputs Gross output is measured as the sum of industry shipment, revenues from repairing and fixing services, and revenues from performing subcontracting works. Intermediate inputs are defined as the sum of raw materials, fuels, electricity, and subcontracting expenditure.

(2) $$\text{CHM}_j = \frac{\text{Chinese imports}_j}{(\text{Value Added}_j + \text{Imports}_j - \text{Exports}_j)}$$

Instrumental Variables

While our motivation of the empirical analysis is to estimate the causal effects of Chinese import competition on the patent outputs, we encounter the possible endogeneity problem: Firm-level innovative activity for the reasons other than Chinese import competition may also shape trade flows, altering the degree of import competition in the industry (for example, more innovative firms might opt to do more offshoring to China in order to facilitate the home innovative operations). For the same reason, the reverse causality is also a possibility: Imports from China may be correlated with industry-wide technology shocks (to some degree, industry-specific fixed effects may take care of this concern, but it might not be sufficient). This makes OLS estimator to be biased and inconsistent.

We use a measure of Chinese (labour) productivity as an instrument for the endogenous Chinese import variables in the technology equation. This IV strategy extracts any exogenous variations affecting Chinese export supply capacity, yet indirectly affecting the level of innovative activity only through the intensified import competition in Japan. This instrument is inspired by the use of an instrument in other studies: Autor et al. (2015) use eight advanced countries[11] to construct the exposure to Chinese import competition as instruments to the US exposures to Chinese imports. The motivation of their IV strategy is to extract supply-side productivity elements in Chinese export performance. However, as pointed out in Autor et al. (2015), their instrument faces the validity challenge whereby industry technological changes among those advanced countries must be separate incidents, in other words, the technological diffusions must be limited across those high income countries. In our implementation of the IV strategy, we directly use the productivity measure (labour productivity) of Chinese industries which has been undoubtedly behind the surge in Chinese export growth, yet indirectly related to firm-level innovative activity. These data are extracted from China Industrial Productivity (CIP) database.[12] There is no strict industry matching to from CIP to JIP industries, so we arbitrary assign the corresponding CIP manufacturing industries to 52 JIP industries.

[11] Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain and Switzerland
[12] http://www.rieti.go.jp/en/database/CIP2015/index.html

5. Empirical Specification and Results

In the empirical implementation, we first follow the linear estimation method, allowing for both fixed effects and an instrumental variable. We then proceed to estimate the count data method (Poisson non-linear ML estimation) noting the nature of patent statistics as the count (*not done yet*). We use the following linear specification to relate firm-level patent growth (for different patent usages separately) to the exposure of Chinese import competition at industries:

$$\Delta \ln (\mathrm{PAT})_{ijt} = \alpha_i + \alpha_{jt} + \beta_1 \mathrm{CHM}_{jt-5} + \varepsilon_{ijt}. \tag{3}$$

where subscripts *i, j* and *t* denote firm, industry and time. For each firm *i* we have the count of patents owned (PAT), the count of those patents in use (USE) and those no-used patents (NON-USE). Within patens in use (USE), we also have breakdown information of patents based on in-house inventions (DEV). We also have the count of patents which are licensed out (LICENSE). These variables form the dependent variables separately in a regression analysis below

The dependent variable is the 5-years (log) change of the patent usage categories as an indicator for firms' innovative activity. An explanatory variable, CHM_{it-5} is in level for the period *t-5*. This linear specification slightly differs from that used in Bloom et al. (2015) wherein 5-years log changes in both dependent (technology) and explanatory (an exposure to Chinese import competition) variables used. The formulation of Eq. (3) is preferred in our data and is intuitively more appealing by noting the fact that making technology (and taking out as patents) requires more time.[13] This specification literally tests the subsequent firms' innovative reaction to Chinese import competition felt in the period *t-5*.[14] Aghion et al. (2009) and Amiti and Khandelwal (2013) also use the similar specification to Eq. (3).

[13] Growth rate is also preferred for a technical reason. Our data on the patent count includes all the cumulative number of patents in which firms claim for the ownership. Hence, by taking growth rate we only account for those newer patents, discounting those older patents.

[14] Even if using the same specification in Bloom et al. (2015), it turns out that the estimation results are quite similar. This goes to show that the persistent impact of Chinese import competition on the technology variables.

The baseline specification also includes both firm fixed effects (α_{it}) and industry-year fixed effects (α_j) to purge any time invariant shocks common in the respective dimensions (such as the unobserved managerial techniques within firms) and industry specific propensity to patent. It has been concretely reported that some industries intrinsically prone to produce more patents than other industries because of the effective patent enforcement (chemical and pharmaceutical).

We also form the patent production function to include other explanatory variables which are drawn from the knowledge production function treating patents as the knowledge output and other firm characteristics as knowledge inputs. They are (log) employment, (log) age of firms, and (log) R&D ratio to sales (R&D intensity).

Results

Table 2 presents benchmark results. We run a set of regressions in OLS with firm and industry-year fixed effects. To aid interpretations of the main results, some descriptive of key variables are presented in Appendix table 1A and 2A. In column (1), it indicates that Chinese import competition overall induce more innovative activities of Japanese firms, though its estimated effects seems to be relatively smaller than the one found in Bloom et al. (2015): 10 percentage point increase in Chinese import competition would result in 0.37% increase in firm-level patents. Across the board, we find the position effect of Chinese import competition except for PAT_DEV and LICENSE.[15]

The most interesting finding is that Chinese import competition also generates more unused patents (NON_USE). It appears that the estimated coefficient is consistently larger than the one estimated for a USE equation (column 2): 10 percentage point increase in Chinese import competition would increase 0.26% increase in unused patents (as against to 0.13% increase in patents in-use). While a reservation about the limitation in this variable withholds (ie, not all unused patents imply for the purpose of 'blocking'), this can be taken as suggestive evidence that Japanese firms would take more defensive reactions to the increased Chinese import competition.

[15] In fact, it is puzzling to see the intensified Chinese import competition would actually lower the rate of in-house invention patents, while it has no statistically significant impacts on patents designed for license out.

The regression result indicates that lower Chinese import competition would trigger more patens based on in-house inventions (by judging from a negative sign in a DEV regression, column 3 in table 2) In addition, Chinese import competition have no statistically significant effects on patented designed for licensing out (LICENSE) in column 4.

Table 2

These above results and associated interpretations are reinforced once we take an instrumental approach **(**table 3). In the first stage regression (not shown), labour productivity has the statistical significance on the level of Chinese import competition.[16] The estimated coefficients in all regressions now show larger effects as compared to the OLS estimates.[17]

Table 3

In table 4, the empirical specification follows a form of the conventional knowledge production function, treating patens as knowledge outputs. Even after we control for relevant firm characteristics, Chinese import competition remains positive and statistically significant. With the firm size (measured by the number of employees), it indicates that smaller firms take out patents more. And older firms (by the age of firms) would lead to more innovative activity (interestingly, the estimated coefficients for firm characteristics withhold much larger than a variable of Chinese import competition): 10 percentage point decrease in employment leads to 4.4% increase of innovative activity. Other than a PAT regression, we only found the effect of Chinese competition to be positive and statistically significant in a NON-USE regression (column 4). Conditioning on relevant firm characteristics, Chinese import competition would produce more defensive nature of patents (unused patents) among Japanese firms.

Table 4

[16] A full set of tests need to carry out to establish the validity of instruments.
[17] In Bloom et al. (2015), the similar results were made as well.

Table 5 sequentially introduce the import competition indicators from other countries. We introduce import competition from Asian NIEs (Singapore, South Korea, Hong Kong China and Taiwan) and separately for those from high-income OECD countries (including US, and high-wage European countries).[18] Overall, the main results remain the same: the increased Chinese import competition would make Japanese firms taking out more patenting, while import competition from other higher wage countries have no statistical significance. This finding also conforms to those found in Bloom et al. (2015). The theoretical intuition drawn from the trapped factor model is that import competition from high wage countries would not substitute for old products which do not change incentives for innovation. Again, we find positive and statistically significance effect on non-use patent (NON-USE), while in other regressions, the sign for CHM has been changed or lost statistical significance as compared to the benchmark estimation.

{follow up}

Estimation of the non-linear panel method

Use the control function approach

6. Conclusion

To be written

[18] In an experimental stage, import competition from other lower wage countries (such as those in Southeast Asia) was included, but it turns out that it is not important, and does not change the estimated coefficient for CHM.

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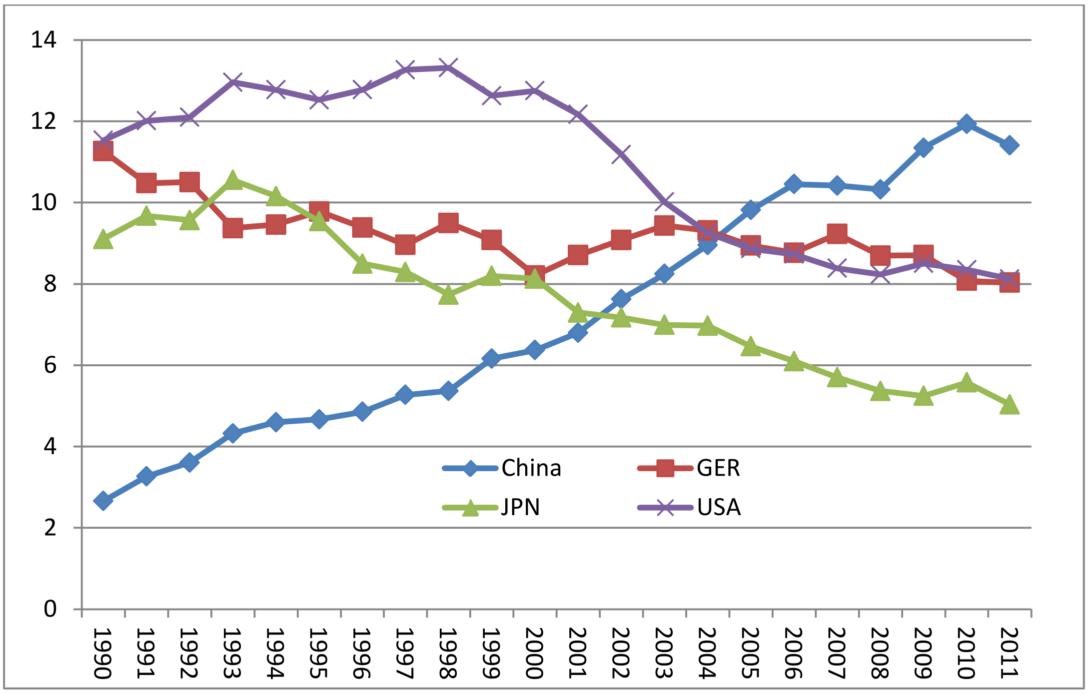
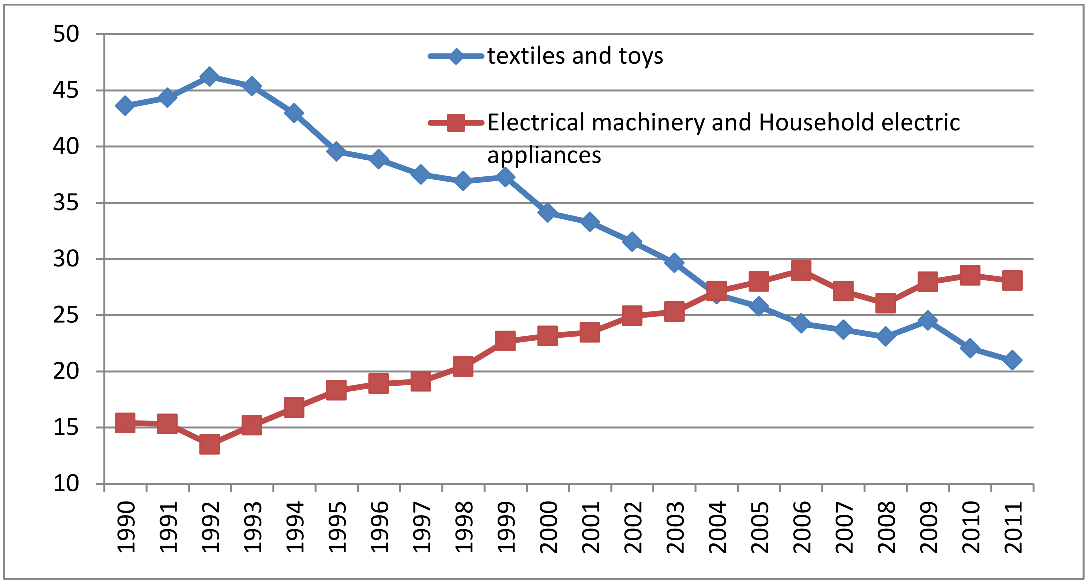
Figure1: The rise of China in world trade, 1990-2011 (%)

Export (percentage share in world exports)



Source: UN Comtrade

Figure 2: Structural Changes in China's export product compositions (% in total exports), 1990-2011



Source: UN Comtrade

Figure 3: Patent Usage and variable definitions

	Variable symbol	Brief explanations and Definitions
Patent Owned	**PAT**	The count of patents owned (including those purchased and cross-licensed) reported by a firm in a given fiscal year. This includes the cumulative count of patents owned by firms, not just patents which are applied for in a given year.
Use (include. licensed out)	**USE**	Those patents in currently use
In-house inventions	**DEV**	Those patents in use based on internal inventions
Non-use	**NON-USE**	Defined as PAT minus USE, including blocking and future commercial use/negotiation
Licensed out	**LICENSE**	Total count of patents which are licensed out. Domestic and International segregation is available as well as the amount of money received

Table 1: Change of Import Competition by source countries/groups in Japanese manufacturing industry, 1994 and 2005

	1994				2005				Change 94-05			
	CHINA	Asian NIEs	SE Asia	USA	CHINA	Asian NIEs	SE Asia	USA	**CHINA**	**Asian NIEs**	**SE Asia**	**USA**
Manufacturing, total	11.4	15.9	10.2	25.7	28.6	12.8	10.9	15.2	**17.2**	**-3.1**	**0.7**	**-10.5**
Top 8 sector in 1994												
Coal products	68.9	13.2	0.0	2.7	92.2	1.5	0.0	0.5	**23.3**	**-11.7**	**0.0**	**-2.2**
Textile products	**48.7**	**15.1**	**8.0**	**5.6**	**76.5**	**3.5**	**4.0**	**2.0**	**27.8**	**-11.6**	**-4.0**	**-3.6**
Miscellaneous ceramic, stone and clay products	34.4	19.1	3.0	13.6	60.4	5.0	3.8	9.6	**26.0**	**-14.1**	**0.9**	**-4.1**
Rubber products	33.4	18.3	10.1	15.7	58.4	6.9	17.2	5.5	**25.0**	**-11.5**	**7.2**	**-10.2**
Leather and leather products	26.5	19.9	5.8	5.2	46.5	1.8	2.7	2.0	**20.0**	**-18.0**	**-3.1**	**-3.3**
Electrical generating, transmission, distribution and industrial apparatus	24.4	24.1	19.5	19.6	47.2	8.5	17.2	10.2	**22.8**	**-15.6**	**-2.3**	**-9.4**
Pig iron and crude steel	23.7	4.0	3.0	7.0	29.7	6.7	1.5	1.7	**6.0**	**2.7**	**-1.5**	**-5.3**
Office and service industry machines	**19.4**	**16.5**	**21.6**	**22.1**	**76.2**	**8.2**	**7.7**	**2.7**	**56.7**	**-8.4**	**-13.9**	**-19.4**
Bottom 8 sector in 1994												
Chemical fibres	1.2	48.9	2.7	26.4	13.9	34.2	15.5	13.3	**12.7**	**-14.7**	**12.8**	**-13.1**
Petroleum products	1.0	22.4	12.0	6.2	2.8	21.1	12.8	2.5	**1.8**	**-1.4**	**0.8**	**-3.7**
Electronic equipment and electric measuring instruments	**0.6**	**3.1**	**0.6**	**63.9**	**10.5**	**3.5**	**4.0**	**38.8**	**9.9**	**0.4**	**3.4**	**-25.1**
Pulp, paper, and coated and glazed paper	0.5	1.7	0.9	40.7	7.3	6.5	13.4	33.5	**6.8**	**4.8**	**12.6**	**-7.1**
Semiconductor devices and integrated circuits	**0.4**	**41.7**	**8.2**	**49.1**	**7.9**	**48.2**	**19.1**	**18.9**	**7.5**	**6.5**	**10.9**	**-30.3**
Printing, plate making for printing and bookbinding	0.4	26.0	1.0	64.7	13.5	11.2	4.5	23.3	**13.1**	**-14.8**	**3.5**	**-41.4**
Tobacco	0.1	0.0	0.0	95.3	0.6	0.1	0.1	89.6	**0.6**	**0.1**	**0.0**	**-5.8**
Motor vehicles	0.0	0.3	0.0	27.7	1.4	1.9	0.9	8.8	**1.4**	**1.7**	**0.9**	**-18.9**

Source: JIP 2013 database

Table 2: Chinese Import Competition and Patent Usage (OLS-FEs), 1994 and 2005

	OLS				
	(1)	(2)	(3)	(4)	(5)
	PAT	**USE**	**DEV**	**NON-USE**	**LICENSE**
CHM_{jt-5}	**0.037***	**0.013***	**-0.019***	**0.026***	**-0.001**
	(0.008)	**(0.007)**	**(0.006)**	**(0.007)**	**(0.001)**
constant	-0.552***	-0.353*	0.359**	-0.447**	0.106***
	(0.191)	(0.198)	(0.169)	(0.171)	(0.033)
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry-Year FEs	Yes	Yes	Yes	Yes	Yes
R-sq	0.394	0.346	0.342	0.298	0.289
N	35200	35200	35200	35200	35200

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by industry. The dependent variable is in five-year log differences of each patent usage type. Chinese imports as a fraction of total industry imports represent an explanatory variable. All columns include a full set of firm and industry-year fixed effects.

Table 3: Chinese import competition and Patent Usage (IV regressions), 1994 and 2005

	Instrumental Variable				
	(1)	(2)	(3)	(4)	(5)
	PAT	**USE**	**DEV**	**NON-USE**	**LICENSE**
CHM_{jt-5}	**0.113*** **	**0.064*** **	**-0.073*** **	**0.077*** **	**-0.009*** **
	(0.004)	**(0.004)**	**(0.004)**	**(0.004)**	**(0.001)**
constant	-1.017***	-0.524***	0.366***	-0.828***	0.065**
	(0.090)	(0.091)	(0.094)	(0.098)	(0.030)
Firm FEs	Yes	Yes	Yes	Yes	Yes
Industry-Year FEs	Yes	Yes	Yes	Yes	Yes
N	35200	35200	35200	35200	35200

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by industry. The dependent variable is in five-year log differences of each patent usage type. Chinese imports as a fraction of total industry imports represent an explanatory variable. All columns include a full set of firm and industry-year fixed effects.

Table 4: Chinese import competition and Patent Usage (OLS with firm-level characteristic controls), 1994 and 2005

	(1)	(2)	(3)	(4)	(5)
	PAT	**USE**	**DEV**	**NON-USE**	**LICENSE**
CHM_{jt-5}	**0.031*** **	**0.010**	**-0.012***	**0.021*** **	**-0.000**
	(0.008)	**(0.007)**	**(0.006)**	**(0.007)**	**(0.001)**
Log (Emp)$_{it-5}$	-0.445***	-0.113	0.023	-0.532***	0.029
	(0.096)	(0.098)	(0.106)	(0.098)	(0.028)
Log(Age) $_{it-5}$	0.517***	0.326***	-0.617***	0.372***	-0.089***
	(0.109)	(0.110)	(0.139)	(0.134)	(0.029)
Log(R&D)$_{it-5}$	-0.253***	-0.372***	-0.696***	-0.032	-0.069**
	(0.056)	(0.101)	(0.118)	(0.075)	(0.026)
constant	0.276	-0.714	2.564***	1.307**	0.266
	(0.597)	(0.589)	(0.556)	(0.634)	(0.165)
R-sq	0.398	0.349	0.350	0.301	0.291
N	35164	35164	35164	35164	35164

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by industry. The dependent variable is in five-year log differences of each patent usage type. Chinese imports as a fraction of total industry imports represent an explanatory variable. All columns include a full set of firm and industry-year fixed effects.

Table 5: Chinese import competition and Patent Usage (OLS with other import competition variables), 1994 and 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	PAT	**PAT**	**USE**	**USE**	**NON-USE**	**NON-USE**	**DEV**	**DEV**	**LICENSE**	**LICENSE**
CHM*jt-5*	**0.036*** **	**0.033*** **	**0.015*** **	**0.007**	**0.025*** **	**0.023*** **	**-0.021*** **	**-0.019** **	**-0.002* **	**0.000**
	(0.008)	**(0.009)**	**(0.005)**	**(0.009)**	**(0.008)**	**(0.007)**	**(0.005)**	**(0.008)**	**(0.001)**	**(0.001)**
NIE*jt-5*	-0.003		0.005		-0.004		-0.007		-0.002	
	(0.008)		(0.008)		(0.005)		(0.007)		(0.001)	
High*jt-5*		-0.007		-0.008**		-0.005		-0.000		0.002*
		(0.006)		(0.004)		(0.008)		(0.005)		(0.001)
constant	-0.494**	-0.144	-0.471*	0.126	-0.351*	-0.170	0.512**	0.365	0.154***	-0.003
	(0.238)	(0.366)	(0.233)	(0.336)	(0.200)	(0.408)	(0.214)	(0.390)	(0.032)	(0.077)
R-sq	0.394	0.395	0.346	0.347	0.298	0.298	0.342	0.342	0.290	0.290
N	35200	35200	35200	35200	35200	35200	35200	35200	35200	35200

Notes: *** denotes 1% significance; ** denotes 5% significance; * denotes 10% significance. Estimation is by OLS with standard errors clustered by industry. The dependent variable is in five-year log differences of each patent usage type. Chinese imports as a fraction of total industry imports represent an explanatory variable. All columns include a full set of firm and industry-year fixed effects.

Appendix table 1A: Descriptive statistics

	PAT	*NON-use*	*USE*	*DEV*	*LICENSE*	*CHM*	*PAT*	*USE*	*NON-USE*	*LICENSE*	**# of firm**
year	Mean	Mean	Mean	Mean	Mean	Mean	Sum	Sum	Sum	*Sum*	**Sum**
1994	109.1	77.2	35.0	27.9	0.4	10.3	46908	16118	30790	200	**6374**
1995	107.2	75.2	32.2	27.8	0.3	12.5	49417	16300	33117	79	**6637**
1996	121.1	86.7	34.6	30.7	0.4	13.7	53485	17650	35835	300	**6614**
1997	98.6	64.3	34.4	91.7	0.6	15.1	53352	17600	35752	800	**6464**
1998	106.4	68.1	38.3	101.2	0.5	16.0	52119	17200	34919	228	**6513**
1999	115.2	73.3	41.9	108.8	0.6	16.8	55909	18692	37217	247	**6447**
2000	50.2	36.6	24.1	40.7	0.9	18.2	43166	9800	33366	344	**6340**
2001	123.3	75.4	47.9	38.9	0.8	20.5	50000	39726	10274	938	**6415**
2002	124.3	78.1	46.3	38.8	0.7	23.0	47000	24670	22330	301	**6269**
2003	142.5	91.9	50.5	41.4	0.7	24.1	48061	20155	27906	350	**5764**
2004	141.9	88.7	53.2	43.1	2.1	26.5	47166	43000	4166	8930	**6088**
2005	130.9	81.0	49.9	43.2	2.3	28.9	42662	34000	8662	10000	**5937**

Source: Own calculation

Appendix table 2A: descriptive statistics for variables used in regressions

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max
PAT	count	75862	113.8	1102.1	0	55909
USE	count	75862	40.4	433.2	0	43000
NON_USE	count	75862	74.5	819.2	0	42662
DEV	count	75862	53.1	653.8	0	55909
LICENSE	count	75862	0.8	49.3	0	10000
emp_total	Unit	75862	629.0	2424.1	50	80500
rd_own	Value in yen	75862	888.4	10266.2	0	527359
est_year	Year	75857	1951.0	111.0	0	2006
CHM	percentage	75862	18.6	16.2	0.02	98

Source: Own calculation