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# Chinese Import Competition and Skill Demand in Japanese Manufacturing*

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## Abstract

This paper examines the hypothesis that manufacturing industries in Japan that have been exposed to import competition from China experience greater skill upgrading by increasing demand for skilled workers. Using an industry panel dataset over the period 1980–2010, we exploit variations of worker' skill categories by occupation, paired with information and communication technology (ICT) investment data in the employment share regression. We find that while import competition from China have shifted from labour intensive to more capital-intensive products, this has not resulted in substituting skilled workers in Japanese manufacturing. Rather, it has had the profound positive effect of raising overall demand for skilled workers. Most of the competition effects were felt among production workers, leaving middle-skilled workers being largely unaffected.

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**Keywords**

Import competition; Japan; manufacturing; labour skill demand; panel dataset

## JEL Classification

C23; F66; J24

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This paper examines the hypothesis that manufacturing industries in Japan that have been exposed to import competition from China experience greater skill upgrading by increasing demand for skilled workers. Using an industry panel dataset over the period 1980–2010, we exploit variations of workers' skill categories by occupation, paired with information and communication technology (ICT) investment data in the employment share regression. We find that while import competition from China has shifted from labour intensive to more capital-intensive products, this has not resulted in substituting skilled workers in Japanese manufacturing. Rather, it has had the profound positive effect of raising overall demand for skilled workers. Most of the competition effects were felt among production workers, leaving middle-skilled workers largely unaffected.

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## 1. Introduction

The well-documented historic rise of China as a trading powerhouse has exerted competitive shocks on the world economy and raised serious concerns among policy circles in industrial economies. These concerns have been directed toward the effects of Chinese import competition as it pertains to the labour market, especially since China joined the WTO in 2001. The literature on this issue has grown extensively to examine the various margins of labour market adjustments at the level of industries, firms, individual workers, and regional economies (Autor, Dorn and Hanson 2013; Autor et al. 2015; Ashournia, Munch and Nguyen 2014; Hummels, Munch and Xiang 2014).[1] The overall findings in the literature regard significant wage depression and labour relocation effects on lower-skilled workers whose tasks can easily be offshored and substituted by Chinese imports.

In this context, this paper examines the relative contributions of Chinese import competition on the observed skill demand shift based on a panel dataset of 52 Japanese manufacturing industries for the period 1980–2009. Using rich information extracted from the Japan Industrial Productivity (JIP) database, we examine the effects of Chinese import competition on industry variation skill demand, while controlling for a proxy for skilled-biased technological changes (SBTC) and other confounding factors. The data coverage is long enough to track an apparent shift in China's comparative advantages from more labour-intensive products toward more capital- and technology-intensive products (to be discussed fully in the next section). This has different implications for the labour market adjustment as the intensity of the competition effects is expected to shift from lower-skilled to higher-skilled workers in Japanese manufacturing.

We use the occupation groups as an imperfect proxy for the skill-intensity. In this framework, we look at the two intertwining forces at play in skill demand: Chinese import competition may exert stronger pressures on lower-skilled jobs via depressed wages that hurt employment prospects. At the same time, information communication technology (ICT) increasingly

[1] The shift in focus from the aggregate industry level has gone through the firm-level stage since the work of Bernard et al. (2006), followed by Mion and Zhu (2013), and Bloom et al. (2011). For a comprehensive review of the literature with this transition, see Hummels et al. (2014).

requires correspondingly skilled workers by shifting labour demand. Both factors would increase demand for higher-skilled workers, but depress demand for lower-skilled workers, while leaving an ambiguous effect on middle-skilled workers. This is our working hypothesis, which we will use for data in a regression analysis.

The organization of this paper is as follows. The next section briefly describes China's export performance with Japan's changing labour market. Section 3 discusses the dataset, followed by the interpretation of the results in Section 4. The final section summarizes the key findings and derives the policy implications.

## 2. 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 a tiny share (around 3%) of world exports. Since then, China's share has gradually increased. Its exports particularly grew rapidly starting around the early 2000s. In the second half of the 2000s, China achieved a formidable export expansion, overtaking Germany as the world's largest exporter and accounting for 10% of world exports. China's export share has grown without any disruptions for a long period of time, while those of Japan, the US, and Germany have not grown during the same period. At the same time, China has become an important economy in the world import market (Figure 1-B). While the US still accounts for the bulk of world imports (around 15%–20%), its share has gradually declined since 2000. By contrast, China's share has been steadily increasing from the lower base accounting to close to 10% in 2011.

**Figure 1 here**

The rise of China in world trade has dramatically changed its specialization. Figure 2 depicts the share of more capital- and technology-intensive electrical machinery and household appliances as compared to the more labour-intensive textiles and toys, showing a shift of comparative advantages from the latter to the former. In 1992, textiles and toys accounted for around 45% of China's total exports. However, its share subsequently dropped to close to 20% in 2011. On the other hand, the export share of electrical machinery and household appliances doubled from less than 15% in 1992 to 30% in 2011. This shift was largely driven by ICT products.

This finding has led others to argue that China has been quickly climbing up the technological ladder. For example, based on the income-weighted export bundle of Chinese goods, Rodrik (2006) contended that China's export capabilities are rapidly converging to the world technological frontier. However, total value trade statistics might be misleading. Indeed, allowing for the role played by processing exports in China's trade structure undermines this observation. That is, it is well known that its export specialization still largely rests on the labour-intensive assembly stage rather than specialization in technological content (Athukorala and Yamashita 2009). China has grown to be an exporter of labour-intensive assembly goods, but still the bulk of technologically advanced parts and components embedded in export goods come from other high-wage countries (such as Taiwan, Japan, the US and Europe). In other words, China's comparative advantages still rest on the labour-intensive segment in capital intensive and high-tech products. These products tend to be mass-market commodities with relatively low unit costs (notebook computers, mobile phones). This explains why Schott (2008) observed that, while the unit price of China's export bundles are relatively low as compared to those of Organisation for Economic Co-operation and Development (OECD) economies, the export similarity index indicates that, over time, China's export bundles started to resemble those of OECD economies.

**Figure 2 here**

***Chinese Import Competition in Japan***

Table 1 sorts the top and bottom 10 industries by degree of Chinese import competition in 1980. In the textile industry, where Chinese firms were considered to have comparative advantages, import competition was keenly felt. Although less than 20% of Japanese textile imports came from China in 1980, by 2009 the share had jumped to 80%. More strikingly, a shift in competition can be observed for the bottom 10 industries (mostly high-tech) that experienced an influx of Chinese imports between 1980 and 2009. Apart from motor vehicles, industries with negligible Chinese import presence in 1980 were, by 2009, subject to intensified competition from China.

**Table 1**

## 3. Empirical Method, Data, and Variable Construction

### *Empirical method*

We follow the conventional estimation specification used in the SBTC literature (Berman, Bound, and Griliches 1994; Machin and Van Reenen 1998; Feestra and Hanson 1999.[2] The baseline specification can be written as follows:

$$Sh_{it} = \alpha_i + \alpha_t + \beta_1 CHM_{it} + \gamma Z_i + \varepsilon_{it} \tag{1}$$

where subscripts *i* and *t* denote industry and time, respectively. The dependent variable (*Sh*) is the employment share of workers according to occupation. In the literature, the dependent variables usually adopt the cost share for a relevant skill category (e.g., skilled worker wage bills divided by the total in a given industry). However, in the case of Japan, the employment indicator seems to be a more appropriate variable for analysing skill upgrading.[3]

We consider the following occupations: technical and professional managers (denoted as Tech) as skilled workers; office, sales and services workers as middle skilled; and assembly and manual labour workers (Production) as lower skilled. A vector of other variables, ***Z***, includes value added (a proxy for the scale economies), ICT capital stock to value added, non-ICT capital stock to value added, R&D intensity, and import penetration from other economies (other than China. Technically speaking, the inclusion of these additional controls may actually induce the "bad controls" problem as described in Angrist and Pischke (2009) - they themselves may be outcomes of the key explanatory variable and therefore bias its estimate. For this consideration, we use the two-year lags of these additional controls.

[2] See Technical Appendix for the derivation of the cost-share equation, as commonly used in this literature.

[3] An alternative measure is the share of skilled workers in the total wage bills of all workers. However, this cannot be computed for the time period covered in this paper because of the unavailability of disaggregated industry-level wage data for nonproduction workers. Two data sources are generally available for compiling the wage bills of Japanese manufacturing nonproduction/production workers: the *Census of Manufactures* (CM) from the Japan Ministry of Economy, Trade and Investment, and the *Basic Survey on Wage Structure* (BSWS) from the Ministry of Health, Labour, and Welfare. The CM includes cash earnings of production and nonproduction workers at the detailed 4-digit level of Japan Statistical Industry Classification. However, since 1990, this information has become unavailable in the CM published data. The BSWS provides wage earnings data for nonproduction and production workers, but they are available only for the total manufacturing industry from 1985 onward.

The adoption of ICT in workplaces has facilitated a shift of production technologies in favour of skilled workers. Autor, Dorn and Hanson et al. (2013) emphasized that ICT substitutes for routine tasks, but complements non-routine cognitive tasks. Furthermore, many routine tasks requiring medium skill sets (or middle-level education), such as bank clerks and telephone operators, have found the demand for their services falling as a result of ICT investment in OECD economies (Michaels et al. 2014). At the other end of the occupational spectrum, jobs requiring non-routine manual tasks (janitors, taxi drivers, and aged care workers) might not be affected much by ICT because of the difficulty of automation in these tasks. In short, this strand of literature revealed that trade (especially imports from low-wage economies) and ICT investment together have contributed to the polarisation of US and Europe labour market skill demand.

The sign of value added, ceteris paribus, depends on whether the expansion of the industry output scale would require more skilled workers. If the estimate coefficients are zero, the hypothesis that the underlying production function is homothetic cannot be rejected. Otherwise, it implies that it is non-homothetic, suggesting the ratio of the optimal inputs demands depend on the level of outputs.

Both the time-specific and industry-fixed effect are also incorporated in order to guard against omitted variables for explaining the employment share of skilled workers in the respective dimensions: the former is needed to control for any unmeasurable (or unobserved) time-invariant heterogeneity, such as industry-specific persistent technological differences or difference in the average management quality. Time-specific effects are also introduced to control for a homogenous form of technological change across industries, but varying across time as well as capturing other macroeconomics shocks.

**Data**

Variables used in the regression analysis are mainly sourced from the Research Institute of Economy, Trade and Industry's (RIETI) Japan Industrial Productivity (JIP 2013) online

database.[4] We use the annual data for the period 1980–2009.[5] The time coverage is ideal since PRC import competition has accelerated in 2000s after its WTO admission in 2001 and the ICT revolution generally started to accelerate in the mid-1990s. The JIP dataset is organized in 3-digit industry levels (52 manufacturing industries) with several useful variables for our purpose, which we describe below.

***Import penetration ratio***

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

$$\text{(2)} \qquad CHN_i = \frac{\text{Chinese imports}_i}{\text{Imports}_i}$$

We also employ the conventional method of constructing Chinese import penetration by normalizing Chinese imports on domestic absorption (i.e., domestic absorption=value added + imports – exports).[6]

$$\text{(3)} \qquad CHN_i = \frac{\text{Chinese imports}_i}{(\text{Value Added}_i + \text{Imports}_i - \text{Exports}_i)}$$

***An indirect measure of skills***

Proper skill intensity measurement must account for educational attainment, on-the-job training, and work experience (Hamermesh 1993). However, there is no single measure to capture these with available datasets. Additionally, the concept of workers' skills is quite vague. This is especially so in the case of the Japanese labour market where strong company orientation makes employees less occupation-conscious as compared with their Western counterparts. Admittedly, either education level, or task-aggregated occupational data usually

[4] http://www.rieti.go.jp/en/database/JIP2013/
The JIP 2013 database is the result of a collaboration between the Research Institute of Economy, Trade and Industry (RIETI) as a part of its "Study on Industry-Level and Firm-Level Productivity in Japan", and the Institute of Economic Research, Hitotsubashi University as a part of its "21st-Century COE Program, Research Unit for Statistical Analysis in the Social Sciences (Hi-Stat)" project. The JIP 2006 can be accessed at http://www.rieti.go.jp/en/database/d05.html. The original version of the JIP database (JIP 2003) was compiled by the Economic and Social Research Institute, Cabinet Office, Government of Japan as part of its research project on "Japan's Potential Growth" and the Hi-Stat project.

[5] The latest year available in the JIP database is 2011. However, import data partitioned by source countries at industry-level are only available to 2009. It should be also noted that annual trade data are only available after 1988.

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

serves as a good proxy for worker skill level. This study adopts the latter approach, using five group occupations. Following Guadalupe (2007), these occupational groups are divided into high, medium, and low skill level as follows: technical workers (systems engineers and computer programmers) and managerial personnel (Tech and Managers) as a skilled group; administrative, advertising and sales workers as medium-skilled group (Office, Sales, Services); and blue-collar (manual workers, assemblers and operational workers) as a less-skilled group. We have these skill groups in each of 52 manufacturing industries for the entire period.

In practice, the occupational divide for workers closely tracks educational attainment. On the whole, the data reasonably support white-collar workers (those fall in medium and high skilled) having a higher education than production workers (blue-collar workers). For example, the employment share of university graduates among total non-production workers in Japanese manufacturing was around 50% in 2004, up from 39% in 1985. The employment share of high school graduates among total nonproduction workers has continued to decline from the mid-1980s, reaching 37% in 2004. The share of junior high school graduates accounted for only 3.4% of nonproduction workers, implying a high concentration in production workers.[7]

***ICT Capital***

We use ICT capital (real stock) divided by value added. ICT capital has been constructed using the perpetual inventory method based on real investment flows, using the quality adjusted price deflator available in JIP data. ICT capital is its stock multiplied by its user cost (see http://www.rieti.go.jp/jp/database/JIP2015/index.html for a detailed discussion of the variable

[7] Of course, occupational segregation is not an entirely satisfactory proxy of workers' skill levels, for a number of reasons. First, there is the misclassification of jobs between nonproduction and production workers. For instance, according to the International Standard Classification of Occupations provided by the International Labour Organization (ILO), line supervisors and product development personnel are included among production workers, whereas delivery truck drivers and cafeteria workers are not. In relation to the misclassification of jobs into skilled/unskilled workers, Lawrence and Slaughter (1993) considered the example of an experienced machine-tool technician with a university degree in computer science who programs the computers driving the tools, and a recent high-school dropout who files the reports and runs mail: if both work for a manufacturing firm, the nonproduction/production distinction will clarify the technician as unskilled and the office runner as skilled. Another reason why occupational segregation is not a good proxy of workers' skill levels is related to the specific context of Japanese employment practice. Under the seniority wage system, workers with a long period of service receive a high salary regardless of educational attainment and job type. As a consequence, it is possible to observe inexperienced workers with skilled jobs receiving lower wages, and experienced workers with less skilled jobs. These considerations make it difficult to retain the assumption of factor substitutability between skilled and less-skilled workers.

construction). We also include non-ICT capital in regressions; taken together, they constitute industry-level capital stock.

***An instrumental variable***

A common problem in the reduced form of the empirical approach is endogeneity: higher skilled worker concentrations might actually result in more intermediate input imports from China. For the same reason, the reverse causality is also a possibility: Chinese imports may be correlated with industry-wide demand for skilled workers (to some degree, industry-specific fixed effects may address this concern, though not if the omitted factors also vary across time). This renders the OLS estimator as biased and inconsistent.

We adopt an instrumental variable (IV) approach to minimize estimation bias. We further measure Chinese labour productivity as an instrument for the endogenous import variables in the employment-share equation. This IV strategy extracts any exogenous variations affecting China's export supply capacity, yet indirectly affects skill demand only through the intensified import competition in Japan. This instrument is inspired by those used in other studies: Autor et al. (2015) used eight advanced countries to construct the exposure to Chinese import competition as pertained to the US. Their IV strategy is to extract exogenous supply-side productivity elements in Chinese export performance. However, as pointed out in Autor et al. (2015), the instrument faces the validity challenge whereby industry skill demand changes among those advanced countries must be separate incidents. In our IV strategy, we directly use the labour productivity measure of Chinese industries that have undoubtedly been behind the surge in export growth. These data are extracted from the China Industrial Productivity (CIP) database. There is no strict industry matching from CIP to JIP industries, so we arbitrarily assigned the corresponding CIP manufacturing industries to 52 JIP industries.

**Other Control Variables**

Other variables are sourced from the JIP 2013 database. Value-added is used to measure the industry output. The ratio of non-IT capital stock to value-added is used to measure capital

intensity of production (denoted as *K*).[8] R&D intensity is also included to control for the industry-specific time-varying technological capacity.

## 4. Empirical Results

### Main Results

We start from running regressions on a simpler version of Eq. (1) with Chinese import competition (*CHN*) as a single control variable (panel A, table 2). To aid in interpreting the results, summary statistics are presented in Appendix table 1A. In each regression, we have the following skill groups in the employment share regressions: Production workers, Office, Sales, Services, Technical, and Managers.

The main finding is that Chinese import competition has the statistically significant positive effect on change in industry skill upgrading, raising the skill demand of Technical workers: a 10% increase in *CHN* would lead to a 6.2 percentage point increase in the employment share of Tech workers (column 5).[9] On the other hand, as expected, the higher intensity of Chinese import competition would depress the employment share of Production workers (column 1). Middle-skilled occupations (Office, Sales, and Service) do not seem to be much affected by Chinese import competition.

This result remains robust even after controlling for other confounding factors such as ICT (and non-ICT) investment capital stock, and R&D intensity and outputs (panel B, table 2). All the estimated Chinese import competition coefficients diminish once other control factors are included. The estimated coefficient on ICT capital intensity suggests that utilization is found to be statistically insignificant with an unexpected negative sign in the skilled employment share (column 5 and 6, panel B of table 2). This finding is markedly different from the commonly found robust complementary relationship between ICT capital utilization and

[8] 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. They are available in real terms in the JIP 2006 database. Real value-added is defined as the difference between real gross output and real intermediate inputs. Capital stock refers to the nominal book value of tangible fixed assets including buildings, machinery tools, and transport equipment.

[9] In the experimental stage, we used two measures of CHN in Eq. (2) and (3), but they are essentially the same; as a result, we only report Eq. (2).

skilled workers in US manufacturing (e.g., Berman, Bound and Griliches 1994). However, this is consistent with a previous study in Japanese manufacturing (e.g., Sakurai 2001. The result for the R&D intensity variable (a proxy for general SBTC) also suggests a negative, but statistically insignificant effect on Technical workers (column 5). By and large, it indicates a dominant factor of Chinese import competition raising skill demand.

The well-known practice of Japanese companies is to undertake assembly activities by exporting parts and components to China (offshoring), while retaining capital- and technology-intensive production (Head and Ries 2002). We therefore add an industry's exports to China as an additional control (panel A, table 3).[10] The export variable has no statistical significance and neither does it change Chinese import competition coefficient. It seems that the intensified Chinese import competition can only trigger the offshoring of basic skill jobs, which can then lead to increased skill intensity at Japanese industries, but no such evidence from exporting.

In panel B of table 3, we introduce industry import penetration from Asian NIEs (Singapore, Republic of Korea, Hong Kong, China and Taiwan), and other high-income economies (those in high wage countries in OECD). Inclusion of this additional import competition seems to magnify the estimated coefficient for China imports for some skill categories. For instance, a 10% increase in Chinese import penetration now accounts for a 13 percentage point decrease in Production employment share (column 1).

Table 4 presents results based on the IV method using the corresponding Chinese labour productivity as an instrument for import competition. The broad result is consistent with the prior finding: Chinese import competition raises demand for skilled occupations, while depressing that of production and manual workers. However, the reported estimated coefficients are much larger than the OLS results in Table 2. Further verification and an instrument validity test need to be implemented (to be done in the revision).

**Table 2 here**
**Table 3 here**
**Table 4 here**

[10] This is constructed similarly to import competition in which we take the ratio of exports to China to industry's overall exports.

## 5. Conclusion

This paper assesses empirically whether Chinese import competition explains skill upgrading in a panel of 52 Japanese manufacturing industries for the period 1980-2009. Our empirical results provide evidence of skill upgrading due to increased Chinese import competition. In particular, Chinese imports have the positive effects of changing the composition of skilled demand towards technical workers and depressing demand for production and manual workers. This result is remarkably robust for the inclusion of ICT capital investment (a proxy for SBTC), export-intensity to China, and import competition from other economies.

The results shown in this paper indicate that Chinese import competition works in favour of skilled workers by raising skill demand. This trend will continue due to an expansion in offshoring activities of Japanese firms. However, there is already an indication that the PRC is also moving up the technological ladder (rather than having specialized in the labour-intensive segment in highly technological goods). Chinese import competition may then yield different pressures to skilled workers. It is less likely that such competition would substitute for skilled workers in Japan. Rather, workers and firms will be placed under much stronger pressure to innovate and further push into the world technological frontier.

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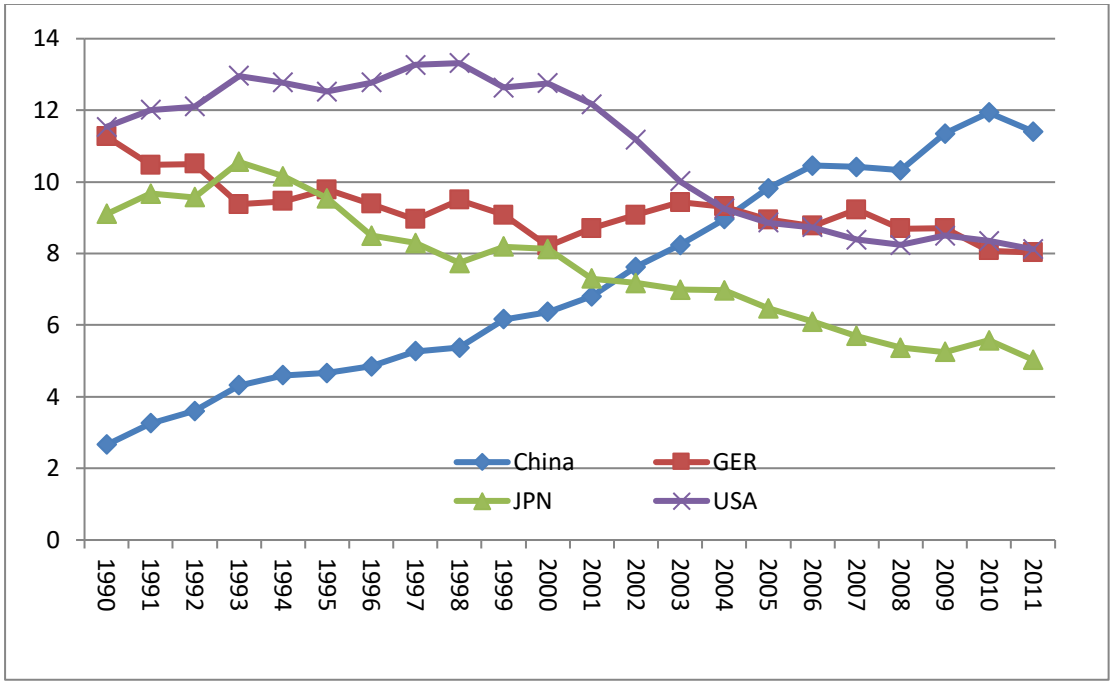
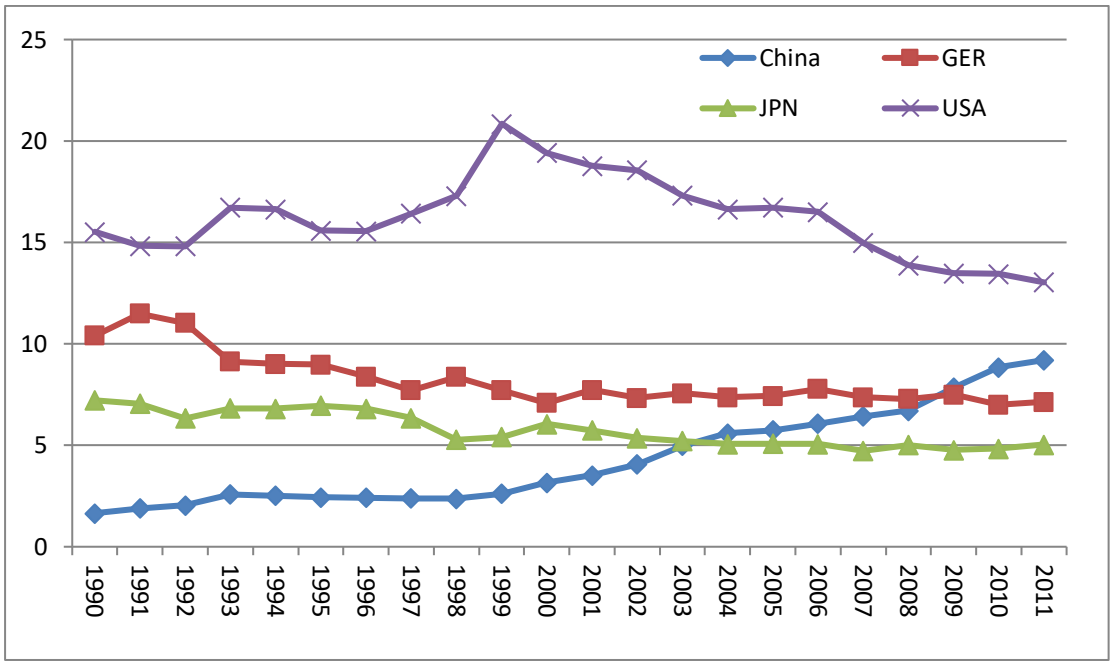
**Figure1: The rise of China in world trade, 1990-2011 (%)**

**A. Export (percentage share in world exports)**

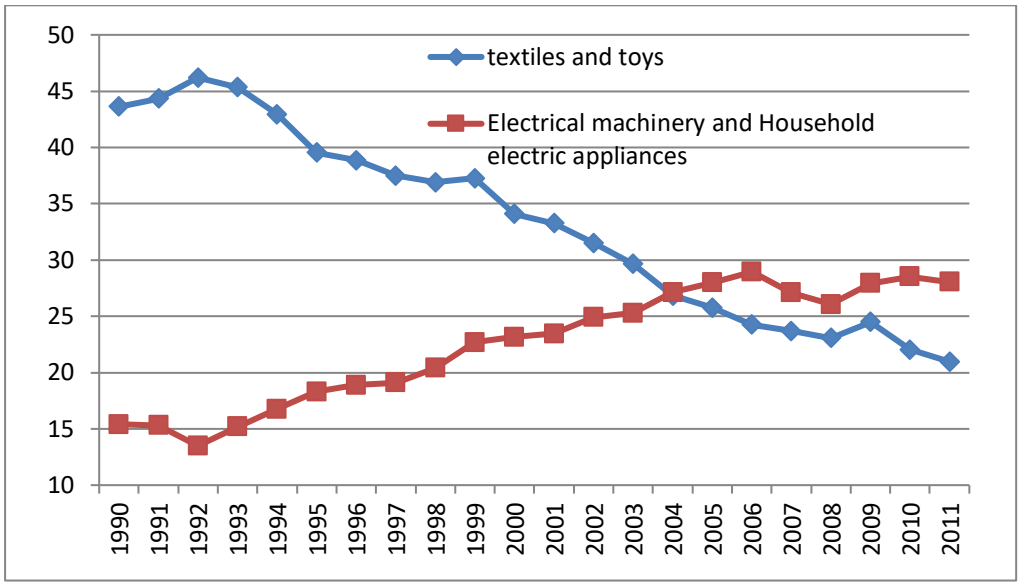



**B. Import (percentage share in world imports)**




Source: UN Comtrade

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




Source: UN Comtrade

**Table 1: Change in Import Competition by source countries/groups in Japanese manufacturing, 1980 and 2009**

| | | China | | Asian NIEs | | Southeast Asia | | US | |
|---|---|---|---|---|---|---|---|---|---|
| JIP industry | | *1980* | *2009* | *1980* | *2009* | *1980* | *2009* | *1980* | *2009* |
| | **The top 10 sectors in 1980** | | | | | | | | |
| 28 | Miscellaneous chemical products | 3.85 | 13.24 | 2.56 | 9.04 | 1.63 | 12.39 | 55.18 | 26.60 |
| 59 | Miscellaneous manufacturing industries | 3.89 | 56.19 | 20.00 | 5.63 | 2.56 | 10.07 | 21.97 | 9.61 |
| 33 | Cement and its products | 4.16 | 44.10 | 20.58 | 27.91 | 0.03 | 14.22 | 15.40 | 2.95 |
| 24 | Basic inorganic chemicals | 5.74 | 30.94 | 5.43 | 8.06 | 1.43 | 5.11 | 22.50 | 18.35 |
| 17 | Furniture and fixtures | 6.85 | 52.44 | 55.74 | 5.77 | 10.64 | 27.08 | 5.16 | 1.58 |
| 34 | Pottery | 7.43 | 48.38 | 5.27 | 6.03 | 0.42 | 17.19 | 17.88 | 5.24 |
| 25 | Basic organic chemicals | 7.94 | 2.40 | 15.73 | 92.28 | 0.00 | 0.00 | 46.67 | 0.04 |
| 15 | **Textile products** | **17.65** | **80.09** | **39.01** | **2.31** | **2.49** | **7.43** | **5.44** | **1.24** |
| 12 | Prepared animal foods and organic fertilizers | 34.33 | 10.72 | 5.01 | 1.95 | 10.52 | 20.27 | 30.51 | 25.71 |
| 31 | Coal products | 36.19 | 64.28 | 28.38 | 4.10 | 0.00 | 0.18 | 23.51 | 4.20 |
| | **The bottom 10 sectors in 1980** | | | | | | | | |
| 27 | Chemical fibers | 0.00 | 16.07 | 45.60 | 35.18 | 1.82 | 14.11 | 32.05 | 12.06 |
| 48 | Electronic data processing machines, | 0.00 | 63.26 | 1.70 | 13.08 | 0.01 | 10.61 | 71.59 | 5.82 |
| 51 | Semiconductor devices and integrated circuits | 0.00 | 10.85 | 20.00 | 50.61 | 12.26 | 11.48 | 55.34 | 19.19 |
| 52 | Electronic parts | 0.00 | 42.39 | 53.71 | 26.55 | 0.05 | 16.60 | 32.56 | 8.60 |
| 56 | Other transportation equipment | 0.00 | 8.86 | 1.40 | 2.46 | 0.57 | 0.52 | 60.58 | 72.40 |
| 45 | Office and service industry machines | 0.00 | 81.59 | 9.08 | 6.91 | 0.33 | 5.79 | 40.77 | 2.36 |
| 50 | Electronic equipment and electric instruments | 0.00 | 24.92 | 1.28 | 5.72 | 0.00 | 3.73 | 77.14 | 29.84 |
| 42 | General industry machinery | 0.01 | 31.10 | 1.28 | 14.84 | 0.07 | 10.29 | 57.06 | 16.74 |
| 55 | Motor vehicle parts and accessories | 0.02 | 29.68 | 3.82 | 9.30 | 3.32 | 18.18 | 39.99 | 8.90 |
| 44 | Miscellaneous machinery | 0.02 | 30.57 | 9.05 | 18.83 | 1.14 | 14.15 | 47.90 | 16.33 |
| 54 | Motor vehicles | 0.02 | 2.72 | 0.02 | 3.96 | 0.01 | 2.84 | 23.82 | 8.40 |

Source: JIP 2013 database

**Table 2:** Effects of Chinese import competition on skill upgrading effects in Japan, 1980-2009

Dependent variable = Employment share by the skill category of workers

| **Panel A** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Prod | Office | Sales | Services | Tech | Managers |
| **Chinese import penetration** | **-0.950**** | **0.150** | **0.171** | **0.014** | **0.622***** | **-0.022** |
| **(1-year lag)** | **(0.432)** | **(0.158)** | **(0.157)** | **(0.011)** | **(0.123)** | **(0.078)** |
| _cons | 70.912*** | 15.937*** | 4.476*** | 0.037 | 4.717*** | 2.887*** |
| | (1.817) | (0.617) | (0.699) | (0.050) | (0.567) | (0.368) |
| Industry Fixed Effects | YES | YES | YES | YES | YES | YES |
| Year Fixed Effects | YES | YES | YES | YES | YES | YES |
| N | 1146 | 1146 | 1146 | 1146 | 1146 | 1146 |
| R-sq | 0.162 | 0.442 | 0.203 | 0.613 | 0.275 | 0.819 |
| F | 10.244 | 16.726 | 13.598 | 57.490 | 11.345 | 51.630 |
| | | | | | | |
| **Panel B** | | | | | | |
| **Chinese import penetration** | **-0.757*** | **0.053** | **0.324*** | **0.021** | **0.282**** | **0.042** |
| **(1-year lag)** | **(0.434)** | **(0.162)** | **(0.180)** | **(0.013)** | **(0.126)** | **(0.055)** |
| Real ICT capital over value added | 0.862 | -0.475 | 0.094 | -0.005 | -0.281 | -0.215 |
| (2-years lag) | (1.092) | (0.592) | (0.379) | (0.013) | (0.679) | (0.193) |
| Real non-ICT capital over value added | -0.001 | 0.001 | 0.000 | -0.000 | 0.000 | -0.000 |
| (2-years lag) | (0.003) | (0.001) | (0.001) | (0.000) | (0.002) | (0.000) |
| Real value added | 0.714 | -0.249 | -0.665** | -0.035 | 0.685 | -0.486 |
| (2-tears lag) | (1.474) | (0.610) | (0.317) | (0.021) | (0.882) | (0.326) |
| Real R&D over value added | 1.611 | -0.609 | -0.792** | -0.015 | -0.217 | 0.013 |
| (2-years lag) | (1.138) | (0.534) | (0.305) | (0.012) | (0.609) | (0.189) |
| _cons | 51.643** | 23.348** | 16.220*** | 0.605* | -2.752 | 10.627* |
| | (22.854) | (9.549) | (5.288) | (0.330) | (14.734) | (5.608) |
| Industry Fixed Effects | YES | YES | YES | YES | YES | YES |
| Year Fixed Effects | YES | YES | YES | YES | YES | YES |
| N | 1078 | 1078 | 1078 | 1078 | 1078 | 1078 |
| R-sq | 0.187 | 0.469 | 0.256 | 0.518 | 0.275 | 0.839 |
| F | 8.743 | 27.105 | 21.780 | 39.246 | 10.103 | 74.823 |

*Notes*: All control variables are in natural logarithms. Weighted least-square (WLS), weights equal to the industries' employment share in total manufacturing. JIP industry clustered standard errors are given in brackets, with statistical significance (two-tailed test) denoted as: *** 1 percent, ** 5 percent, and * 10 percent.

**Table 3:** Effects of Chinese import competition on skill upgrading effects in Japan, 1980-2009

Dependent variable = Employment share by the skill category of workers

| **Panel A** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Prod | Office | Sales | Services | Tech | Managers |
| **Chinese import penetration** | **-0.960**** | **0.156** | **0.153** | **0.013** | **0.649***** | **-0.019** |
| **(1-year lag)** | **(0.449)** | **(0.166)** | **(0.156)** | **(0.011)** | **(0.138)** | **(0.079)** |
| CHN export exposure | -0.077 | 0.045 | -0.127 | -0.007 | 0.192 | 0.027 |
| (1-year lag) | (0.388) | (0.161) | (0.142) | (0.006) | (0.227) | (0.051) |
| _cons | 71.180*** | 15.779*** | 4.916*** | 0.062 | 4.052*** | 2.793*** |
| | (2.486) | (0.962) | (0.822) | (0.057) | (1.099) | (0.434) |
| Industry Fixed Effects | YES | YES | YES | YES | YES | YES |
| Year Fixed Effects | YES | YES | YES | YES | YES | YES |
| N | 1142 | 1142 | 1142 | 1142 | 1142 | 1142 |
| R-sq | 0.162 | 0.442 | 0.211 | 0.617 | 0.279 | 0.819 |
| F | 12.571 | 24.484 | 6.721 | 65.386 | 13.340 | 41.338 |
| | | | | | | |
| **Panel B** | | | | | | |
| **Chinese import penetration** | **-1.315**** | **0.206** | **0.440*** | **0.029*** | **0.604**** | **0.027** |
| **(1-year lag)** | **(0.647)** | **(0.285)** | **(0.228)** | **(0.017)** | **(0.240)** | **(0.080)** |
| Import penet. NIEs | 0.495 | -0.166 | -0.076 | -0.008 | -0.117 | -0.129 |
| (2-years lag) | (0.602) | (0.248) | (0.127) | (0.008) | (0.257) | (0.108) |
| Import penet. High income | 0.883 | -0.382 | -0.472** | -0.018 | -0.000 | -0.043 |
| (2-years lag) | (1.068) | (0.414) | (0.227) | (0.017) | (0.530) | (0.112) |
| _cons | 39.157 | 26.645*** | 17.370*** | 0.762* | 7.400 | 8.108* |
| | (24.305) | (9.530) | (5.275) | (0.436) | (10.389) | (4.231) |
| Industry Fixed Effects | YES | YES | YES | YES | YES | YES |
| Year Fixed Effects | YES | YES | YES | YES | YES | YES |
| N | 1006 | 1006 | 1006 | 1006 | 1006 | 1006 |
| R-sq | 0.139 | 0.426 | 0.252 | 0.523 | 0.187 | 0.850 |
| F | 5.313 | 8.710 | 8.335 | 21.166 | 4.989 | 57.107 |

*Notes*: All control variables are in natural logarithms. Weighted least-square (WLS), weights equal to the industries' employment share in total manufacturing. JIP industry clustered standard errors are given in brackets, with statistical significance (two-tailed test) denoted as: *** 1 percent, ** 5 percent, and * 10 percent.

**Table 4:**
IV estimates of the effects of Chinese import competition on skill upgrading effects in Japan, 1980-2009
Dependent variable = Employment share by the skill category of workers

| **Panel A** | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Prod | Office | Sales | Services | Tech | Managers |
| **Chinese import penetration** | -2.450*** | 0.757*** | 0.299*** | 0.028*** | 1.207*** | 0.093** |
| **(1-year lag)** | (0.368) | (0.148) | (0.079) | (0.007) | (0.182) | (0.038) |
| _cons | 76.593*** | 11.826*** | 5.912*** | 0.286*** | 0.532** | 3.341*** |
| | (0.637) | (0.251) | (0.275) | (0.018) | (0.224) | (0.075) |
| N | 1078 | 1078 | 1078 | 1078 | 1078 | 1078 |
| F | 934.097 | 893.080 | 415.693 | 73.779 | 801.526 | 451.637 |

*Notes*: All control variables are in natural logarithms. Weighted least-square (WLS), weights equal to the industries' employment share in total manufacturing. JIP industry clustered standard errors are given in brackets, with statistical significance (two-tailed test) denoted as: *** 1 percent, ** 5 percent, and * 10 percent.

**Table 1A: summary statistics**

| | Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Skill measures | Prod | 1488 | 65.97 | 8.74 | 38.74 | 83.90 |
| | Office | 1488 | 16.20 | 4.00 | 6.85 | 33.33 |
| | Sales | 1488 | 5.12 | 2.52 | 1.35 | 15.02 |
| | Service | 1488 | 0.20 | 0.16 | 0.00 | 1.10 |
| | Tech | 1488 | 6.61 | 4.66 | 0.24 | 25.11 |
| | managers | 1488 | 4.19 | 1.42 | 1.04 | 8.42 |
| Controls | PRC import penetration | 1146 | 1.78 | 1.93 | -8.09 | 4.58 |
| | Real ICT capital over value added | 1392 | 2.48 | 1.23 | -2.88 | 6.09 |
| | Real non-ICT capital over value added | 1392 | 236.84 | 355.13 | 0.59 | 5648.12 |
| | Real value added | 1392 | 14.21 | 0.99 | 9.35 | 17.99 |
| | Real R&D over value added | 1363 | 3.55 | 1.45 | 0.21 | 8.02 |
| | Import penet. From Asian NIEs[1] | 1104 | 21.44 | 2.17 | -5.76 | 25.61 |
| | Import penet. From high income[2] | 1104 | 23.05 | 1.76 | 13.57 | 25.53 |
| | Export to the PRC | 1148 | 1.61 | 1.36 | -5.84 | 4.16 |

*Notes*: 1. All control variables are in logarithm. Asian NIEs are Singapore; Republic of Korea; Hong Kong, China; and Taipei,China. 2. High income countries are those in OECD countries.

## A2. Derivation of cost-share equation

First, the cost minimization framework is described. Industry minimizes a quasi-fixed (short-run) cost function, $C(\mathbf{w}, y)$, in which output ( $y$ ) and $\mathbf{w}$ are a vector of production factors such as capital ( $k$ ) as a fixed factor (as exogenous) and more-skilled and less-skilled labor as variable factors. The cost function takes a translog form, which is the second order Taylor series approximation linearly homogenous function with a concave in factor prices, as per Christensen et al. (1973). The translog short run cost function ( $C$ ) with a subscript z denoting industry is then written as follows (a time subscription is dropped for convenience):

(A.1)

$$\begin{aligned}\ln c_z = \alpha_0 &+ \sum_{i=1}^{M} \alpha_i \ln w_{z,i} + \sum_{k=1}^{K} \beta_k \ln x_{z,k} + \\ &\frac{1}{2}\left( \sum_{i=1}^{M}\sum_{j=1}^{M} \gamma_{i,j} \ln w_{z,i} \ln w_{z,j} + \sum_{k=1}^{K}\sum_{l=1}^{K} \delta_{k,l} \ln x_{z,k} \ln x_{z,l} \right) \\ &+ \sum_{i=1}^{M}\sum_{k=1}^{K} \phi_{i,k} \ln w_{z,i} \ln x_{z,k}\end{aligned}$$

where $w_i$ refers to the optimally chosen variable factor prices with subscripts denoting $i, j = 1, \cdots M$ and $x_k$ denotes either the quantities of fixed inputs (capital), outputs or other structural parameters with subscripts $k, l = 1, \cdots K$ .

Equation (A.1) requires the following linear parameter restrictions to satisfy the linearly homogenous property with respect to variable factor costs ( $w_i$ ):

$$\gamma_{i,j} = \gamma_{j,i}\,, \quad \delta_{k,l} = \delta_{l,k}\,, \quad \sum_{i=1}^{M} \alpha_i = 1\,, \text{ and } \sum_{i=1}^{M} \gamma_{i,j} = \sum_{i=1}^{M} \varphi_{i,k} = 0\,.$$

Differentiating equation (A.1) with respect to $\ln w_i$ yields the cost share of variable factor $i$ : $\dfrac{\partial \ln C_z}{\partial \ln w_i} = \left(\dfrac{\partial C}{\partial w}\right)\left(\dfrac{w_i}{C_z}\right)$ where $\left(\dfrac{\partial C}{\partial w}\right)$ refers to factor demand for input $i$ by

Shephard's lemma. It follows that $\frac{\partial \ln C_z}{\partial \ln w_i} = \frac{E_i w_i}{C_z} = S_{z,i}$ is equal to the share of factor $i$ in total costs, denoted by $S_{z,i}$ (where $E$ is a factor $i$ employment). In the end, it yields a cost share equation of variable factor of input $i$:

(A.2) $$S_{z,i} = \alpha_i + \sum_{j=1}^{M} \ln w_{z,j} + \sum_{k=1}^{K} \varphi_{i,k} \ln x_{z,k} \quad \text{and} \quad \sum_{i=1}^{M} S_{z,i} = 1$$

Equation (A.2) relates the cost share of variable factor i to factor prices and the output level and fixed input capital. A cost share for variable factor $j$ can be similarly derived. By assuming the coefficients of independent variables are equal across all industries, equation (A.2) can be pooled cross-industry and by time.