KEO Discussion Paper No.158

# Import competition and product churning: Evidence from Japanese plant-product-level data

Flora Bellone and Toshiyuki Matsuura

January 19, 2021

# Import competition and product churning: Evidence from Japanese plant-product-level data[1]

Flora Bellone
Universite Cote d’Azur, CNRS, GREDEG

Toshiyuki Matsuura
Keio University

Abstract

This study examines how Japanese firms change their product portfolio in response to the surge of imports from China. Using the comprehensive Japanese plant-product level panel data set, we examine the impact of import competition on their product churning behavior. We found that the import competition pressures do affect the product churning for multi-product plants. Besides, the negative effects of import competition are mitigated by increased export opportunities. This effect is more pronounced especially the year before 2007. However, its impact on the plant-level reallocation is somewhat limited. Negative effects on plant-level sales and exit behavior are observed only for a single product-plant.

Keyword: Import competition, Product Portfolio, Local Product Relatedness
JEL classification: F61, L25, D22

1 This research was supported by a grant-in-aid from Zengin Foundation for Studies on Economics and Finance. This study utilizes the data of the questionnaire information based on “Census of Manufacture” (Ministry of Economy, Trade and Industry, METI) and “Economic Census for Business Activities” (Ministry of Internal Affairs and Communications), which is arranged in the project “A Study of Free Trade Agreements” undertaken at Research Institute of Economy, Trade and Industry (RIETI). We also utilize the plant-id converter for the Census of Manufacture, which is provided by RIETI.

## 1. Introduction

Recently, the surge of imports from China has attracted policymakers' attention in many developed countries. For example, a series of studies by David Autor and his colleagues reveal that rising Chinese import to the US has a substantial negative impact on the local labor market. (Autor et al. 2013, Acemoglu et al. 2016). For example, Autor et al. (2013) demonstrate that 55 percent of the decline in US manufacturing employment from 2000 to 2007 can be explained by rising exposure to imports from China. Furthermore, the exposure to Chinese imports induces a decline in wages, a higher unemployment ratio, and increases in transfer payments through multiple federal and state programs. Some studies present similar evidence for Europe. For example, Malgouyers (2017) finds that France also experienced a decline in manufacturing employment due to import competition from China. Furthermore, it polarized the local employment in the manufacturing sector. Similar patterns of the impact of Chinese imports on local employment are found by Balsvik et al. (2015) for Norway, and by Donoso et al. (2014) for Spain.

Turning to Japan, we see the increases in the import share from China and the decline in manufacturing worker share. According to Japan Industry Productivity (JIP) Database 2015, during the period from 1990 to 2012, while the share of import from China to total domestic demand increased from 1.9% to 5.3%, the share of manufacturing in total employment has decreased from 23% to 16%. The straightforward question is how does rising imports from China affect Japanese manufacturing industries. In particular, is it more significant because of the geographical proximity of Japan to China?

Existing studies regarding the effect of imports from China on employment in Japan present somewhat different results compared with the ones in the U.S. or Europe. For example, Tomiura (2003) investigates the impact of the increase in imports from low wage countries using Japanese detailed industry-level data and finds a negative impact on employment in some industries, but he reports that the economic impact is not so large. A more recent study by Taniguchi (2019) examines the impact of rising Chinese imports on the Japanese local labor market at the prefecture-level following the methodology used in Autor et al. (2013) and finds that the impact of imports from

China is not negative; rather she found a positive effect in case of intermediate goods import.

Although the labor market effect of rising Chinese import is not significant, fierce competition from low wage countries forces some firms to switch their products or give up producing existing products. This paper focuses on the effect of China import competition on plant level or plant-product level sales and survival decision using comprehensive firm-plant-product level data in Japan. To precisely identify import competition pressure, we matched six digit-level plant-product level data with international trade data. And then we examine what kind of firm/plants are more likely to reorganize their product portfolio and their production facilities. In this paper, we also shed light on regional characteristics, such as local wage and local comparative advantages.

Our work is related to two strands of the literature. The first one is the impact of import competition from low-wage countries such as China. As we mentioned above, many papers examine the impact of Chinese imports on the labor market, mainly in developed countries. The second is the impact of trade liberalization on within-firm reallocation for multi-product firms. Bernard et al. (2010) use the US plant-product level data set and shows that product switching behavior is comparable to the entry and exit of the plant. Mayer et al. (2014) examine the impact of trade on within-firm reallocation and focus on the key role of "core products". They find that in response to import competition, firms tend to drop "non-core products" retaining "core products" only. The paper which is more closely related to ours is Iacovone et al. (2013). They utilize the Mexican plant-product level data set and examine the impact of Chinese imports on within-firm reallocation at the plant-product level.

The rest of the paper is organized as follows. In section 2, we present an empirical model and explain our data source, data, and variable construction procedures. After presenting some descriptive statistics in section 3, the estimation results are shown in section 4. After confirming the robustness of the results in section 5, we conclude this paper in section 6.

## 2. Estimation strategies

### 2.1 Empirical Model

Following Iacovone et al. (2013), we estimate the following equation;

$$y_{\mathrm{ikrt}} = \beta_1 X_{it-1} + \beta_2 IMP_{kt-1} + \beta_3 IMP_{kt-1} * X_{it-1} + \beta_4 Z_r + \mu_i + \lambda_t + \varepsilon_{\mathrm{it}}$$

where $y_{\mathrm{ikrt}}$ is a plant or plant-product-level outcome variable. Specifically, we use product exit, plant exit, or log of plant or plant-product sales. *IMP* is the import competition measure, which is proxied by Chinese import share in total import for sector *k*. *X* is plant characteristics. We include logged number of employees, logged number of products, and within plant sales share of focal products (*Share*). In the literature on multi-product firms and international trade (e.g., Bernard et al. 2011, Mayer et al. 2014), a product with the largest sales within a firm is regarded as the most profitable product or "core product." To control within-plant heterogeneity across products, we include the interaction term of *Share* with import competition measure, *IMP*. Finally, we also include regional characteristics, *Z*. We include the average wage by prefecture and local product relatedness (*LPR*) measure.

For the plant-product-level impact, we separately estimate the multi-product plant and single-product plant. As pointed out by Iacovone et al. (2013), the results for multi-product plants can be interpreted as within plant reallocation. In contrast, samples for the single-product plant are the subset of plant-level data, and the results for these plants are considered as the impact on small plants.

## 2.2 Data and Variable Construction Procedure

Our primary data sources are the longitudinal data sets of the Census of Manufacture (COM)[2]. The COM is an establishment-level data set compiled by the Ministry of Economy, Trade, and Industry (METI). The COM data covers all plants with more than four or more employees located in Japan and includes information on plant characteristics, such as their location, number of employees, amount of tangible assets, the value of shipments, and four-digit-level sector

[2] The survey in year 2011 was conducted as "Economic Census for Business Activities" (Ministry of Internal Affairs and Communications) in place of the COM. We complement the data of the year 2011 from Economic Census.

classification.[3] The COM also provides the plant-product-level shipment data at six-digit-level commodity classification. In this study, we use the plant-product-level data set over the period from 1997 to 2014.

To identify plant exit or plant-product exit, we use a unique identification number given to each plant. Exiting plants are defined as the plants that are observed at time t - 1 but not at t. A limitation of the data is that it is not possible to distinguish firm closure from exclusion from the census due to a fall in employment below four employees. We find that some plants stop reporting to the census but re-start to report a few years later. We construct exit dummy variables referring to the final reporting year of each plant.

Our import competition measure is the share of Chinese import in total import at product-level. To compute the share of Chinese imports, we use trade data at HS 9-digit of Japanese customs. Since HS 9-digit classification is often revised, we use the concordance table of HS 9-digit code constructed by Aoyagi and Ito (2019). Then, the concordant HS 9-digit import data are, matched with the product code of the Census of Manufacture at 6-digit. The concordance table between the COM six-digit commodity data and HS nine-digit trade data is constructed in Baek et al. (2019).[4] In our matched data set, 1125 products are included[5].

One may be concerned that the coefficient of the Chinese import share suffers from the endogeneity bias if the demand shock in Japan affects both imports from China to Japan and domestic product sales. We follow the identification proposed by Autor et al. (2013) and use the shares of Chinese imports to the U.S. and Europe as instrument variables. We believe the supply shock in China, such as an improvement of market access from China to developed countries and productivity enhancement of Chinese firms, do affect both imports from China to Japan and that to Europe and the U.S. However, the demand shock in Japan may not have any effect on the

---

3 Unfortunately, the information on the international trade activates at plant-level is quite limited. It provides the share of export revenue in total shipment from 2001. However, there is no information for import side.

4 The concordance table is provided by Dr. Youngming Baek.

5 In original data set in the COM, we have 2378 products as of the year 2014. However, not all "products" in the COM are tradable goods (e.g., revenue from modification and repair fee or piecework) or cannot be matched with trade statistics (e.g., miscellaneous office paper products).

Chinese imports to Europe and the U.S. Therefore, we expect these variables will work as valid instruments.

In addition to the China import intensity, we take into account three international trade measures. The first is the share of exports from Japan to China. According to Dauth et al. (2014), who investigates the impact of Chinese imports on German local labor markets, negative impacts of import competition are mitigated by export demand from China, and it contributes to retaining manufacturing sectors in Germany. Since Japan's exports to China is as large as its imports from China, increased export opportunities may mitigate the negative impact of import competition pressures as in Germany. To control this effect, we include the share of exports to China in total exports as an additional variable. The second is the measure of imported inputs from China. China imports may have a positive effect if firms become able to access cheaper and a larger variety of imported inputs. To take into account this effect, we use Japanese Input-Output tables and calculate Chinese import share weighted with input-output coefficients.[6] This measure is frequently used in previous studies, such as Acemoglu et al. (2016) and Iacovone et al. (2013).

The third is the import competition or export opportunity measures from/to other developing countries. Japan's imports from low-wage countries are not only from China but also other developing countries such as Southeast Asian countries. To take into account the increase in imports and exports from/to other developing countries, we calculate the import and export share from/to ASEAN and include additional variables. Since these additional export and import variables are considered as endogenous variables, we estimate the model with the instrument variables which are constructed in the same manner with the share of Chinese imports.

Regarding variables for plant, plant-product, and regional characteristics, we include the number of employees at plant-level, within-plant product share, the average wage by region, and the local comparative advantage[7]. The wage is calculated using plant-level data

[6] We used the input coefficient in the year of 1995 which is included in Linked Input-Output (IO) Table for 1995-2000-2005. To link the sector classification of Linked IO Table with the COM commodity classification, we use the concordance table between 2005 Basic IO Table and the COM commodity classification, which is provided in the Appendix of 2005 Basic IO Table. Following Acemoglu et al. (2016), we choose 1995 IO table because the input-output linkages in 1995 might be less likely to be affected by the import from China.

[7] One may be interested in how productivity measure such as total factor productivity (TFP)

in the COM by prefecture. As for the measure of local comparative advantages, we use the product relatedness measure, which is developed by Hidalgo et al. (2007). This measure indicates the similarities or complementarities among products based on underlying capabilities, which can be production factors, skills, knowledge base, institutions, business networks, etc. Hausmann and Hidalgo (2011) show that product relatedness plays an important role in product diversification and product upgrading at the country level. More recent studies relate the product-level product relatedness measure with regional comparative advantages and examine its impact on growth path at the regional level or at the firm or plant-levels (Boschma et al. 2012, Poncet and Starosta Valdemar, 2015, Hazir et al. 2019).[8]

## 3. Data Overview

Table 1 presents the breakdown of plants concerning their association to single or multi-plant firms, and the number of products. Two things are noteworthy. First, there is a decline in the total number of plants from 1997 to 2014, from 218,000 to 138,000 plants. Around 60% of the decline in the total number of plants is accounted for by the decline in the number of single-product plants that are single-plant firms (column (2)). Second, the number of multi-products plants, especially of those belonging to multi-plant firms, is relatively stable (column (6)). As a result, the share of these plants has slightly increased from 6% to 7%.

== Table 1 ==

Corresponding plant characteristics, such as the average number of employees per plant and the average number of products per plant are shown in Table 2. Plants owned by multi-plant firms are larger than those that are single-plant firms. In particular, the average size of single-product

affects product churning. However, the information on the amount of tangible asset is restricted to plants with 30 or more employees, which prevent us from calculating TFP.

8 The details of variable definition of LPR is explained in Appendix A.

plants that are single plant firms (column (1)) is one-tenth of the size of multi-product plants owned by multi-product firms. Another noticeable thing is that the average size of single-plants is increasing over time. This fact is probably due to the increase in the plant shutdown of small firms. Looking at the number of products for multi-product firms owned by multi-plant firms, it is decreasing while the one for plants owned by single-plant firms is slightly increasing, implying that larger firms are more actively reorganizing their product portfolio.

== Table 2 ==

Table 3 presents the transition matrix that indicates the probabilities of plants starting with *n* products at the beginning of the period (1997 or 2007) ending with *m* products at the end of the period (2007 or 2014) — the sum of probabilities equals one along the rows. Plants producing five products or more are categorized as 5+.[9] We also calculate the share of plants that have reduced or increased their number of products during the observation window as compared to the number of products in the initial period. Off-diagonal elements in the lower right are the shares of plants that have reduced the number of products, and those in the upper left have increased the number of products.

We split our samples into two groups according to the degree of the competition; one includes the plants facing the above-median import competition, the other covers those facing the below-median competition. Import competition is measured by the changes in Chinese import share in total import at the four digit-level. We examine whether plants facing severe competition have a higher probability of reducing their products or not. Cells highlighted in red indicate the probability is higher than the one in an alternative competition status in the same period.

Three things are noteworthy. First, regardless of periods and competition status, the

[9] The analysis presented in Table 3 underestimates transitions because plants with an initial portfolio including five or more products are grouped together. Expansions in their portfolio are not accounted for, whereas contractions are accounted for only when the resulting portfolio contains less than five products.

probabilities of plants increasing their number of products are at most 12%, implying that the majority of the plants in our samples have reduced the number of products. Second, looking at the transition matrix, in both periods, cells highlighted in red concentrate in the lower right, indicating plants facing higher competition pressure tend to reduce the number of products. The share of plants reducing their products in the high competition sector is higher than that in the low competition sector in most cases. Third, comparing the share of plants reducing their products between two periods, while the shares in the period from 1997 to 2007 are around 50-70%, those in the period from 2007 to 2014 are 40-57%. It implies changes in portfolio size is more significant for the first period than for the second one.

== Table 3 ==

## 4. Main Results

We start to examine the impact of Chinese imports at the plant-product and plant-level. The results are presented in Table 4. While Column (1)-(4) presents the product churning for multi-product plants, Column (5)-(8) and Column (9)-(12) are the results at plant-product-level for single-product plants and those at plant-level, respectively. As we mentioned, since product level estimations for single-product firms boil down to the plant level, the results in Column (5)-(8) are interpreted as a plant-level impact for single-product plants.[10]

The coefficients of import competition are negative for sales and positive for product exit or plant exit, regardless of estimation method, OLS or IV. Looking closely at the coefficients of *IMP* in IV estimation, *IMP* significantly affects the plant-product sales and plant-product exit rate. (column (2), (4)). Plant-level impact emerges only for single product firms (plant-product-level impact for single product firms, column (6), (8)). We do not find any significant impact on plant-level estimation (column (10), (12)). As for regional characteristics, for product or plant sales (product or plant exit), we expect a positive (negative) impact for *LPR* and a negative (positive)

[10] Note that the import share is measured at six-digit level for plan-product-level estimation while it is calculated at four-digit level for plant-level estimation.

impact for the regional wage. However, regarding regional wage, we do not find any systematic effect. For *LPR*, there is a significant negative impact in the case of plant survival, implying that plants located in the region with local comparative advantage are less likely to exit compared to plants located in other regions.

== Table 4 ==

## 5. Robustness checks

We conduct several robustness checks.[11] First, to consider export demand shock, we include the share of exports from Japan to China as an additional control variable. However, even if we consider the export opportunities, the major findings related to import competition measure do not change; international trade shock does affect plant-product churning or plant-level sale and survival only for the single-product plant. Second, we also control the measure of imported inputs from China. However, we do not find any significant impact. In panel (b), the shares of import and export from/to ASEAN are included as additional controls. Again, there seems to be no systematic effect on plant-product or plant-level sales and survival. Finally, we spilled our samples into two periods; the period from 1997 to 2007 and the period from 2008 to 2014 to explore whether the impact of import competition changes over time or not. In the former period, we find similar results to those in our baseline estimates; Import and export from/to China significantly affect plant-product churning or plant-exit for single-product plants. However, in the later period, we do find almost no significant impact on product churning and plant exit behavior. These results may imply that the firm's restructuring in response to the increases in imports has been completed by the mid or the end of the 2000s.

## 6. Concluding remarks

This study examines how Japanese firms change their product portfolio in response to the surge of imports from China. Using the comprehensive Japanese plant-product level

---

[11] For more details, see the earlier version of this paper; Bellone et al. (2019).

panel data set, we examine the impact of import competition on firms' product churning behavior. We found that the import competition pressures do affect the product churning for multi-product plants. Besides, the negative effects of import competition are mitigated by increased export opportunities. This effect is more pronounced, especially the year before 2007. However, its impact on the plant-level reallocation is somewhat limited. Negative effects on plant-level sales and exit behavior are observed only for a single product-plant.

We also explore the role of local factors such as local wage and local comparative advantages, measured by local product relatedness (LPR) indicator. While there is no systematic result regarding local wage, LPR has a significant impact on plant-exit, implying that plants located in the regions with local comparative advantages are less likely to exit from the market.

## References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G., 2016, Import Competition and the Great US Employment Sag of the 2000s, Journal of Labor Economics, 34(S1), 141-198.

Aoyagi, T. and Ito, T., 2019, Did the Least Developed Countries Benefit from Duty-free Quota-free Access to the Japanese Market?, Japan and the World Economy, 49: 32-39.

Autor, D., Dorn, D., and Hanson, G., 2013, The China Syndrome: Local Labor Market Effects of Import Competition in the United States, American Economic Review, 103(6) 2121-2168.

Baek, Y., Hayakawa, K., Tsubota, K., Urata, S., and Yamanouchi, K., 2019, Tariff Pass-Through in Wholesaling: Evidence from Frim-level Data in Japan, RIETI Discussion Paper, forthcoming.

Balsvik, R., Jensen, S., and Salvanes, K G., 2015, Made in China, Sold in Norway: Local Labor Market Effects of an Import Shock, Journal of Public Economics, 127, 137-144.

Bernard, A., Redding, S.J., Stephen, J., Schott, P K., 2010, Multi-Product Firms and Product Switching, American Economic Review, 100(1), 70-97.

Bernard, A., Redding, S.J., Stephen, J., Schott, P K., 2011, "Multiproduct Firms and Trade Liberalization," The Quarterly Journal of Economics, Oxford University Press, vol. 126(3), pages 1271-1318.

Bellonem F., Hazir, Matusura, T., Import competition and product churning: Evidence from Japanese plant-product-level data, RIETI Discussion Paper, 19-E074.

Boschma, R., Minondo, A., and Navarro, M. (2012). Related Variety and Regional Growth in Spain. Papers in Regional Science, 91(2).

Dauth, W., Findeisen, S., and Suedekum, J., 2014, The rise of the east and the far east: German labor markets and trade integration, Journal of the European Economic Association, 12(6), 1643-1675.

Donoso, V., Martin, V., and Minondo A., 2015, Do Differences in the Exposure to Chinese Impacts Lead to Differences in Local Labour Market Outcomes? An Analysis for Spanish Provinces, Regional Studies, 49(10), 1746-1764.

Hausmann, R., Hidalgo C., 2011, The Network Structure of Economic Output, Journal of Economic Growth, 16, 309-342.

Hazir C. S., F. Bellone and C. Gaglio, 2019, Local Product Space and Firm Level Churning in Exported Products, Industrial and Corpora Change, *forthcoming*.

Hidalgo, C. A., Klinger, B., Barabasi, A, L., Hausmann, R., 2007, The Product Space Conditions the Development of Nations, Science, 317, 482-487.

Iacovone, L., Rauch, F., and Winters, L., 2013, Trade as an Engine of Creative Destruction: Mexican Experience with Chinese Competition, Journal of International Economics, 89, 379-392.

Malgouyers, C., 2017, The Impact of Chinese Import Competition on Employment and the Wage Distribution: Evidence from French Local Labor Markets, Journal of Regional Science, 57(3), 411-441.

Mayer, T., Melitz, M., and Ottaviano, G., 2014, Market Size, Competition and the Product Mix of Exporters, American Economic Review, 104(2), 495-536.

Poncet, S. and Starosta de Waldemar, F. (2015). Product relatedness and firm exports in china. The World Bank Economic Review, 29(3):579–605

Taniguchi, M., 2019, The Effect of an Increase in Imports from China on Regional Labor Markets in Japan, Journal of the Japanese and International Economics, 51, 1-18.

Tomiura E., 2003, The impact of import competition on Japanese manufacturing employment, Journal of the Japanese and International Economies, 17(2), 118-133.

## Appendix A Variable definition of LPR

In this appendix, we explain how we construct the product relatedness measure. The product relatedness measure we use is so-called the output-based approach utilizing international trade data at the product-level. First, following Ballassa (1965), we define RCA (Revealed Comparative Advantage) index for product *j* in country *k* as follows;

$$RCA_{\mathrm{jk}} = \begin{cases} 1\ if\ \frac{a_{jk}}{\Sigma_k a_{jk}} / \frac{\Sigma_j a_{jk}}{\Sigma_j \Sigma_k a_{jk}} > 1 \\ 0 \quad othewise \end{cases},$$

where a is the value of product *k* exported by country *j*. Then, we calculate the conditional probability *P* that country has RCA in product k given that it has RCA in product m

$$P(k|m) = \frac{\#\ of\ counries\ with\ RCA\ in\ both\ k\ and\ m}{\#\ of\ countries\ with\ RCA\ in\ m}$$

Based on this conditional probability, Hidalgo et al. (2007) define the relatedness indicators as follows;

$$\phi_{km} = \min\{P(k|m),\ P(m|k)\}.$$

Our relatedness indicator for selected products is presented in Table A1. The pair of Computer and TV&Radio is 0.264, while the one for the pair of Bread and TV&Radio is only 0.05 Next, to link the regional data set, we calculate the RCA index using product-level data by region;

$$RCA_{\mathrm{jl}} = \begin{cases} 1\ if\ \frac{s_{jl}}{\Sigma_k s_{jl}} / \frac{\Sigma_j s_{jl}}{\Sigma_j \Sigma_k s_{jl}} > 1 \\ 0 \quad othewise \end{cases},$$

where *s* is the sales of product *k* in region *l*. Using the conditional probability calculated with international trade data, local product relatedness is defined as follows;

$$LPR_k^l = \Sigma_{n=1,n\neq k}^N \left( \frac{\phi_{kn}}{\Sigma_{n=1,n\neq k}^N \phi_{kn}} RCA_{ln} \right).$$

For the calculation of the international trade based RCA index, we use the BACI data set prepared by CEPII. And region-product-level RCA index is calculated with the COM product-level data aggregated at the prefecture-level.

Table 1. The number of plants by Single-Multiple Plant status and Single-Multiple Product Status

| | Single-plant firm | | | | | | Multi-plant firm | | | | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) Total | | (2) Single product | | (3) Multi-product | | (4) Total | | (5) Single product | | (6) Multi-product | | |
| 1997 | 186,448 | (86%) | 121,730 | (56%) | 64,718 | (30%) | 31,539 | (14%) | 19,549 | (9%) | 11,990 | (6%) | 217,987 |
| 2002 | 161,352 | (85%) | 106,542 | (56%) | 54,810 | (29%) | 28,118 | (15%) | 17,344 | (9%) | 10,774 | (6%) | 189,470 |
| 2007 | 146,573 | (84%) | 96,348 | (55%) | 50,225 | (29%) | 27,167 | (16%) | 17,007 | (10%) | 10,160 | (6%) | 173,740 |
| 2014 | 113,968 | (83%) | 73,242 | (53%) | 40,726 | (30%) | 23,735 | (17%) | 14,730 | (11%) | 9,005 | (7%) | 137,703 |

Source: A matched database of Census of Manufacturer with International trade data

Note: Figures in parentheses are the share of focal plants to the total number of plants in a given year.

Table 2. The average number of employees and the average number of products for multi-product plant

| | # of employees | | | | | | # of products | | |
|---|---|---|---|---|---|---|---|---|---|
| | Single-plant firm | | | Multi-plant firm | | | | | |
| | (1) Single product | (2) Multi-product | (3)Total | (4) Single product | (5) Multi-product | (6)Total | (7) Total | (8) Single plant firm | (9) Multi-plant firm |
| 1997 | 17.25 | 26.35 | 20.41 | 61.95 | 195.63 | 112.77 | 1.92 | 1.77 | 2.68 |
| 2002 | 17.75 | 26.39 | 20.68 | 64.41 | 181.30 | 109.20 | 1.90 | 1.76 | 2.63 |
| 2007 | 20.22 | 29.04 | 23.24 | 77.78 | 193.37 | 121.01 | 1.92 | 1.80 | 2.49 |
| 2014 | 22.32 | 31.45 | 25.58 | 81.29 | 190.16 | 122.60 | 2.01 | 1.89 | 2.52 |

Source: A matched database of Census of Manufacturer with International trade data

Table 3. Transition matrix of the number of products

**1997-2007**

**High competition**

| | 0 | 1 | 2 | 3 | 4 | 5+ | | Share of plants that reduce # of products | Share of plants that increases # of products |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 51.05 | 43.01 | 4.35 | 1.13 | 0.35 | 0.11 | 100 | 51.05 | 5.94 |
| 2 | 47.56 | 19.07 | 26.02 | 5.44 | 1.44 | 0.47 | 100 | 66.63 | 7.35 |
| 3 | 45.01 | 10.93 | 14.95 | 21.43 | 5.96 | 1.71 | 100 | 70.89 | 7.67 |
| 4 | 41.97 | 7.29 | 9.75 | 14.82 | 20.78 | 5.39 | 100 | 73.83 | 5.39 |
| 5+ | 36.97 | 4.38 | 6.43 | 10.48 | 15.96 | 25.78 | 100 | 74.22 | |
| Total | 49.39 | 34.19 | 9.52 | 4.08 | 1.91 | 0.92 | 100 | | |

**Low competition**

| | 0 | 1 | 2 | 3 | 4 | 5+ | | Share of plants that reduce # of products | Share of plants that increases # of products |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 52.34 | 41.9 | 4.44 | 0.97 | 0.26 | 0.09 | 100 | 52.34 | 5.76 |
| 2 | 47.83 | 15.44 | 29.22 | 5.72 | 1.46 | 0.33 | 100 | 63.27 | 7.51 |
| 3 | 47.18 | 7.65 | 12.7 | 24 | 6.56 | 1.91 | 100 | 67.53 | 8.47 |
| 4 | 47.1 | 3.34 | 6.2 | 12.53 | 24.54 | 6.3 | 100 | 69.17 | 6.3 |
| 5+ | 36.64 | 2.71 | 4.26 | 7.79 | 16.58 | 32.02 | 100 | 67.98 | |
| Total | 50.49 | 31.54 | 9.7 | 4.45 | 2.53 | 1.29 | 100 | | |

**2007-2014**

**High competition**

| | 0 | 1 | 2 | 3 | 4 | 5+ | Total | Share of plants that reduce # of products | Share of plants that increases # of products |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 40.29 | 53.84 | 4.39 | 1.08 | 0.27 | 0.12 | 100 | 40.29 | 5.86 |
| 2 | 35.28 | 18.83 | 37.65 | 5.96 | 1.73 | 0.55 | 100 | 54.11 | 8.24 |
| 3 | 31.74 | 9.04 | 16.33 | 32.48 | 7.74 | 2.67 | 100 | 57.11 | 10.41 |
| 4 | 27.56 | 5.64 | 8.12 | 17.03 | 29.76 | 11.89 | 100 | 58.35 | 11.89 |
| 5+ | 22.3 | 4.71 | 4.42 | 7.87 | 14.35 | 46.36 | 100 | 53.65 | |
| Total | 37.95 | 41.5 | 11.44 | 5.02 | 2.39 | 1.7 | 100 | | |

**Low competition**

| | 0 | 1 | 2 | 3 | 4 | 5+ | Total | Share of plants that reduce # of products | Share of plants that increases # of products |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 39.78 | 54.01 | 4.81 | 0.97 | 0.28 | 0.14 | 100 | 39.78 | 6.2 |
| 2 | 35.47 | 15.95 | 40.24 | 6.31 | 1.49 | 0.53 | 100 | 51.42 | 8.33 |
| 3 | 33.41 | 7.05 | 14.75 | 34.74 | 7.5 | 2.53 | 100 | 55.21 | 10.03 |
| 4 | 32.89 | 4.08 | 5.79 | 14.07 | 32.44 | 10.73 | 100 | 56.83 | 10.73 |
| 5+ | 26.23 | 2.61 | 3.75 | 6.71 | 14.34 | 46.35 | 100 | 53.64 | |
| Total | 37.85 | 39.56 | 12.43 | 5.52 | 2.82 | 1.82 | 100 | | |

Table 4. Baseline results

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Plant-product-level for multi-product plant | | | | Plant-product-level for single-product plant | | | | Plant-level | | | |
| | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV | OLS | IV |
| VARIABLES | log(sales) | log(sales) | Product-exit | Product-exit | log(sales) | log(sales) | Product-exit | Product-exit | log(sales) | log(sales) | Plant-exit | Plant-exit |
| log (# of products)t-1 | 0.0880*** | 0.0849*** | -0.0166*** | -0.0162*** | | | | | 0.0507*** | 0.0509*** | -0.00837*** | -0.00838*** |
| | (0.0102) | (0.0104) | (0.00142) | (0.00143) | | | | | (0.00487) | (0.00461) | (0.000986) | (0.000968) |
| log (employees)t-1 | 0.503*** | 0.508*** | -0.0921*** | -0.0925*** | 0.560*** | 0.557*** | -0.126*** | -0.125*** | 0.639*** | 0.641*** | -0.0188*** | -0.0190*** |
| | (0.0126) | (0.0150) | (0.00489) | (0.00505) | (0.00992) | (0.0105) | (0.00435) | (0.00450) | (0.0174) | (0.0167) | (0.00252) | (0.00264) |
| Sharet-1 | 1.512*** | 1.511*** | -0.00144 | -0.00124 | | | | | | | | |
| | (0.0338) | (0.0334) | (0.00134) | (0.00135) | | | | | | | | |
| Local Product Relatedness | -0.101 | -0.142 | 0.00312 | 0.00662 | -0.0305 | -0.0568 | 0.00185 | 0.00644 | -0.178 | -0.168 | -0.0330*** | -0.0338*** |
| | (0.0886) | (0.0916) | (0.00853) | (0.00893) | (0.0552) | (0.0680) | (0.0158) | (0.0180) | (0.110) | (0.110) | (0.00729) | (0.00736) |
| log (regional wage)t-1 | 0.114** | -0.0224 | -0.0874*** | -0.0738*** | 0.210*** | 0.115* | -0.136*** | -0.118*** | 0.129* | 0.162** | 0.0563*** | 0.0535*** |
| | (0.0567) | (0.0826) | (0.0167) | (0.0177) | (0.0510) | (0.0639) | (0.0193) | (0.0221) | (0.0745) | (0.0672) | (0.0114) | (0.0115) |
| IMPt-1 | -0.101** | -1.210*** | 0.00496 | 0.112* | -0.0720 | -0.979*** | -0.000903 | 0.167*** | -0.650* | -0.0161 | 0.0102 | -0.0439 |
| | (0.0506) | (0.304) | (0.0107) | (0.0656) | (0.0498) | (0.263) | (0.0153) | (0.0563) | (0.364) | (0.0757) | (0.0103) | (0.0353) |
| Plant-Product FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No | No |
| Plant FE | No | No | No | No | No | No | No | No | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1,534,330 | 1,534,313 | 1,697,514 | 1,697,497 | 1,730,743 | 1,730,738 | 1,944,412 | 1,944,408 | 2,890,514 | 2,890,514 | 2,998,423 | 2,998,423 |
| Kleibergen-Paap F | | 2614.738 | | 2966.341 | | 2986.066 | | 3575.3 | | 15000 | | 15000 |
| Hansen J test p-value | | 0.537 | | 0.8294 | | 0.2359 | | 0.503 | | 0.1163 | | 0.9038 |
| R-squared | 0.945 | 0.944 | 0.684 | 0.683 | 0.953 | 0.952 | 0.593 | 0.592 | 0.947 | 0.947 | 0.273 | 0.273 |

Note: Plant-product fixed effects are included. Robust standard errors in parentheses, which are clustered on the four-digit product level for plant-product estimation and two-digit industry level for plant-level estimation. ***, ** and * indicate the statistical significance at 1%, 5% and 10%.

Table A1. Relatedness indicator for selected products

| | | 971 | 1164 | 1711 | 3014 |
|---|---|---|---|---|---|
| 971 | Bread | | | | |
| 1164 | Shirt | 0.146 | | | |
| 1711 | Oil refinery | 0.150 | 0.105 | | |
| 3014 | Radio&TV | 0.056 | 0.129 | 0.096 | |
| 3031 | Computer | 0.096 | 0.076 | 0.100 | 0.264 |