Adjusting to China competition: Evidence from Japanese plant-product-level data

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Abstract

This study examines how the product mixes of Japanese manufacturing plants have been impacted by the rise of China imports over the period 1997-2014, and how the way plants are embedded in their local environment mitigates this causal relationship. We find evidence that China import competition induced both product downsizing and product exit within Japanese manufacturing plants. Moreover, we find that those negative effects differ across plants according to various plant characteristics including the spatial organization of their parent firm. Finally, we show that both product survival and product sales are positively impacted by external agglomeration economies, but these effects are strong for standalone plants only, and almost non-existent for plants affiliated to spatially compact multi-plants firms.

Keywords: Import competition, Product Portfolio, Local Product Relatedness.

JEL codes: F61, L25, D22.

1 Introduction

The surge of imports from China has attracted policymakers' attention in many developed countries. One of the main concerns is related to the pressure Chinese imports put on manufacturing plants and jobs both at national

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and local levels. Indeed, a lot of uncertainty exists about the prospects for manufacturing activities within high-wage countries facing new competition from low-wage countries.

Until now, research has mainly focused on the labor markets impacts of Chinese imports and striking evidence has started to be accumulated from a large variety of countries. By contrast, much less is known about how manufacturing plants in industrialized countries are finely adjusting their production capacities, and especially their product range to Chinese competition. Did manufacturing plants in high wage countries downsize or drop products because of the new competitive pressure of China imports? If so, have some plants been more resilient than others, and why? In particular, did plants embedded in local environment featuring strong agglomeration economies resist better? Also, did plants react differently depending on the spatial organization of their parent firm?

Our paper answers these questions for the case of Japan using a plant-level dataset that covers detailed product level information on the universe of Japanese manufacturing plants operated over the period 1997-2014. We investigate the response of Japanese manufacturing plants to the surge of imports from China in terms of product exit and sales. We also investigate to what extent those responses are asymmetric across heterogeneous plants, which differ in various technological, organisational and spatial dimensions. Those explorations are possible thanks to the richness of the plant-level dataset we work with, which allows us to build a proxy for the technological ability of the plant, to link each plant to the larger organisational structure it belongs to when the plant is part of a multi-plant corporation, and to locate each plant at the level of commuting zones in Japan.

By exploring the heterogeneous responses of Japanese manufacturing plants to China competition, our paper makes a twofold contribution to the literature. First, we provide the first micro evidence on the impact of China competition on product churning in the case of Japan. Second, we explore the heterogeneous response of Japanese plants not only in relation to their own characteristics, as some of the previous literature has done, but also in relation to the characteristics of the location they are settled in, and to the type of corporate organizations they belong to. We put new emphasis on the spatial organization of corporate structures and on the interactions of plants with their local environment to explain plant product portfolio dynamics, and thus shed new light on spatially uneven impact of China competition in high wage countries.

On the theoretical side, two strands of economic literature motivate our hypotheses that plant-level adjustments to China competition shows a high degree of diversity depending altogether on its technological, organizational and spatial characteristics. First, the models of heterogeneous firms and trade have shown that incumbent firms react differently to common aggregate shocks and in particular to trade liberalization shocks (see in particular Bernard et al. (2011) and Mayer et al. (2014)) depending on their intrinsic technological ability. Based on these models more productive firms can be expected to be more resilient to new competitive challenge than less productive firms.

The second strand provides the premises to the hypotheses about the impact of both organisational and spatial characteristics. First, in the economic geography literature, a few theoretical articles model firms' local interactions in order to predict trade related outcomes at the firm level (Rauch and Watson (2003), Hazir et al. (2019))[1]. While none of these previous contributions specifically investigate the responses to adverse competitiveness shocks, recent contributions show that the impact of geographic clustering on those responses could be theoretically ambiguous. Indeed, some authors argue that clustering generates economic benefits, thereby enhancing firms' resilience to adverse shocks (Delgado and Porter (2016)). On the other hand, a competing view is that clusters make firms more vulnerable to such shocks as they become a source of inertia (Pouder and John (1996), Martin and Sunley (2003)). As we will see, this theoretical ambiguity echoes some of our empirical results. Finally, at the interface of both the firm organization and the economic geography literature, Behrens and Sharunova (2015) develop a conceptual framework in which the heterogeneity in the spatial organization of firms explain why some plants might depend less on external agglomeration benefits than others. One of their predictions for which we find support is that plants belonging to multi-plant firms depend less on external agglomeration benefits than comparable standalone plants.

Turning to our empirical strategy, we frame our research into a conceptual framework designed to allow plants owned by different types of corporate organization structures to face different trade-offs as regards the use of their internal and external resources. It is also designed to allow for some forms of agglomeration economies that prevail among plants located nearby. Then, we built our estimation strategy on two previous contributions in the literature. First, to identify import competition pressure at the product level and to deal with its endogeneity, we follow Autor et al. (2013) and use the shares of Chinese import to the U.S. and to Europe to instrument the import competition variable. Second, to examine what kind of plants are more likely to reorganize their product portfolio and their production facilities, and how they do so, we build on Iacovone et al. (2013), who examine the impact of Chinese imports on the product churning of Mexican manufacturing firms. As regards to this former empirical set up, our main departure is in distinguishing plants with respect to the spatial organization of their parent firms and in investigating the role of agglomeration economies.

The rest of the paper is organized as follows. In section 2, we present our conceptual framework in more detail. In section 3, we review the relevant empirical literature. In section 4, we present our data sources and provide key figures on our sample of plants. In section 5, the econometric specification, variable construction procedures, and estimation are explained. In section 6, we present the estimation results and robustness checks. Finally,

[1]Rauch and Watson (2003) develop a model in which the local agglomeration of exporters increases the buyer's information on the quality of the suppliers, and then favor larger orders and hence more important exports at the firm-level. Hazir et al. (2019) extend the model by Bernard et al. (2010) to predict that multi-product firms should be more likely to expand their export portfolio towards new products that are closely related to the core competencies of their local environment

we conclude this paper in section 7.

2 Our conceptual framework

Our conceptual framework is in line with the new trade models featuring heterogeneous multi-product firms facing trade liberalization shocks as for instance Baldwin and Gu (2009) and Bernard et al. (2011). In these background models, single-plant firms decide about the range of their product scope depending on the toughness of their competitive environment and on their own characteristics. There are two key predictions of these models. First, more efficient firms tends to have a larger product scope. Second, firms facing tougher competition pressure tend to refocus their product portfolio on their core products, and consequently tend to drop their most peripheral products. These models, however, do not predict the asymmetric shifts across and within plants that we describe in relation to the spatial organization of the parent firm and to the presence of local agglomeration economies, as both complex firm structure and economic geography dimensions are absent.

While our research builds on these theoretical premises, it also requires some departure from them as we need to acknowledge plant heterogeneity in terms of their organizational features, and also to allow for non market cross-plants interactions. To do so while keeping our set-up tractable and connected to the earlier literature, we first allow firms to be multi-location and multi-plant in our conceptual framework, but we keep firm-level decisions about their corporate structure as exogenous to the plant-level outcomes we focus on.

Specifically, we make the simplifying assumption that the initial spatial organization of firms is given at the time their plants have to adjust to the trade shock. Under this assumption, the plant-level outcomes of China competition can depend on the spatial organization of the focal plant's parent firm, but not the other way around. We can then allow our focal plants to drop or downsize some less profitable products depending on the specific transition costs it faces. For instance, in our framework, plant-product outcomes can depend upon the reallocation opportunities the parent firm can offer to the plant resources.

We also assume that the decision about production facilities are taken at the plant-level even in multi-plant firms. Doing so, we follow the same assumption that Baldwin and Gu (2009) and Iacovone et al. (2013) implicitly make when testing the firm-level predictions of their respective theoretical models by relying on plant-level data. This assumption finds some support in empirical studies demonstrating that in manufacturing firms decision-making is often decentralized[2]. This simplifying assumption is also in line

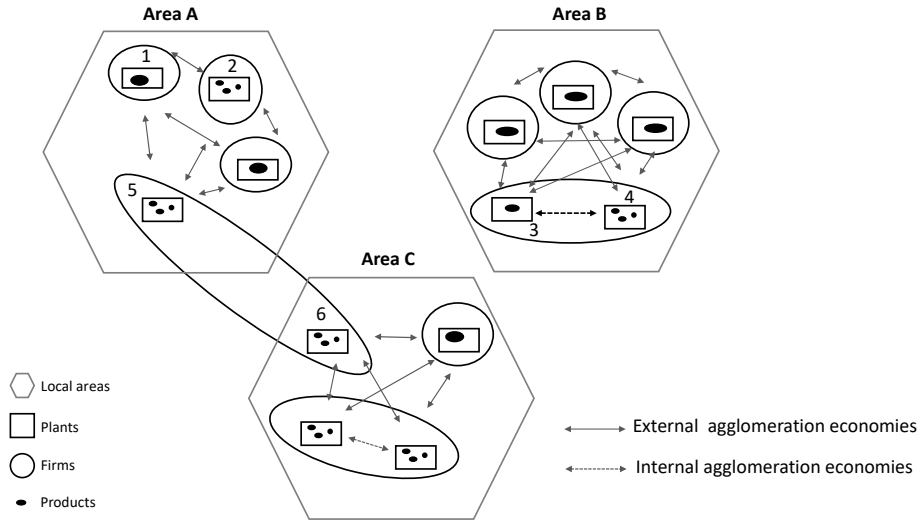
[2]See in particular the management literature which investigates the distribution of manufacturing decision making in multi-plant networks and find that decentralized decisions structures are as prevalent as centralized ones in a large variety of manufacturing sectors (Olhager and Feldmann, 2018). A fair objection to this simplifying assumption in our case study could be that Japanese organizations are usually depicted as fairly centralized ones (see, for instance, Bloom et al. (2012) for a comparison of the degree of centralization of

with the fact that plants are allowed, in our framework, to interact among each other both within and outside their firm boundaries.

Finally, in our conceptual framework, locality is perceived as a product network, where the nodes are products and ties refer to the extent that two products rely on common or complementary capabilities. In this network, some nodes represent the core products of the locality, which refer to the products produced with revealed comparative advantage at the regional-level. We assume that externalities arising from core products of the locality diffuse through this network in such a way that the externalities are stronger for products that are more similar to core products in terms of underlying capabilities. These externalities can work through sharing, learning and matching mechanisms (Duranton and Puga, 2004) and affect the intrinsic product characteristics as well as firms' marginal costs.

All in all, in our conceptual framework, a plant decision to downsize or drop a product will be impacted by the degree of the competitive pressure on that product, the own plant efficiency, the organizational structure of the plant's parent company, and the plant's local environment which determine to what extent each plant-product can benefit from external agglomeration economies. Figure 1 illustrates the main possible organizational configurations for a focal plant. Plant 1 and Plant 2 in the figure are respectively mono-product and multi-product plants owned by single-plant firms. Plant 3 and Plant 4 are owned by compact multi-plant firms, as all the plants of the parent firm are located in the same area. Plant 5 and Plant 6 are multi-product plants owned by dispersed multi-plant firms.

manufacturing decision process in multi-plants networks across a variety of countries including Japan). However, earlier management literature has also shown that while formal centralization in Japan is high, de facto decentralization is usually low and in particular lower than that in the U.S. (Lincoln et al., 1986).



Notes: Authors' own drawing.

Figure 1: Possible geographical pattern of standalone and affiliated plants

3 Overview of the empirical literature

Our paper primarily relates to the literature that investigates, through the lens of microdata, the impact of import competition from low-wage countries on manufacturing activities operated in high wage countries. In this research line, the bulk of the literature has focused on labor market outcomes. For example, a series of studies by David Autor and his colleagues have relied on large scale workers dataset to reveal that rising Chinese import to the U.S. had a substantial negative impact on the local labor markets (Autor et al., 2013; Acemoglu et al., 2016) [3].

Considering the impact of Chinese imports on the production mix of firms located in high wage countries, some earlier literature has shown that US manufacturing firms have changed their activity mix in response to import from low wage countries even before the accession of China to WTO. For example, Bernard et al. (2006) show that over the 1977-1997 period, US manufacturing plants were more likely to switch industries in response to trade with low-wage countries than in response to trade with high wage countries. Liu (2010) confirmed this finding for the U.S. public firms, by

[3]Since these seminal works, studies on other advanced economies have also shown significant negative impacts for France Malgouyres (2017) Norway Balsvik et al. (2015) , Spain Donoso et al. (2015) and Portugal Branstetter et al. (2019). Interestingly, Taniguchi (2019) find no negative labor market outcomes of China import competition in the case of Japan.

showing that large multi-industry U.S. firms tend to exit from their most peripheral production lines and to concentrate on their core production activities as a response to increased trade liberalization. However, this paper does not focus on China competition *per se*, and does not provide direct evidence at the product level.

More recently, a bunch of papers has shown that some manufacturing firms in high wage countries upgraded their technology in response to Chinese competition (Bloom et al., 2016; Mion and Zhu, 2013; Utar, 2014). More specifically, these papers show that increased competitive pressures from China make firms to adopt production processes that are more intensive in skilled and non-production workers (Mion and Zhu, 2013; Utar, 2014), and to rely more on innovation (Bloom et al., 2016; Utar, 2014)[4]. A last series of papers investigates how exporting firms in high wage countries adapt their portfolio of exported products in response to higher China competitive pressure. In particular, Martin and Mejean (2014) show that French manufacturing firms responded by upgrading the quality of their exported products. Fontagné et al. (2018) find that French and Italian firms responded by dropping some products from their export basket. They also show that more stable products within a firm's export basket are also more resilient to China competition [5].

However, none of these previous contributions scrutinize the overall product mix of manufacturing firms, and how it has been impacted by the rise of Chinese imports[6]. By contrast, Iacovone et al. (2013) addresses this issue on a large sample of manufacturing plants operating in a middle-income country, namely Mexico. The paper examines the impact of Chinese import on within-firm reallocation at the plant-product level. They show that sales of smaller Mexican plants and more marginal products were compressed and were more likely to cease, whereas those of larger plants and core products seemed relatively impervious to the shock. However, the way China competition impact manufacturing firms in a high wage country, such as Japan, can be very different from the way it impacts firms in an emerging economy such as Mexico [7].

Considering the role that the local environment plays in supporting the competitiveness of firms or products, some earlier work in economic geography has already brought useful insights. First, a couple of recent studies

[4]As regards the innovation channel, some robustness issues have recently been raised by Campbell and Mau (2020) who show that the within firm channel in Bloom et al. (2016) becomes insignificant when estimation biases are controlled for. This implies China competition spurred U.S. innovations through cross-firm reallocations only.

[5]A stable product refers to the product that is more prevalent over time across firm' export destinations. It is not necessarily the core product of the firm, which is defined as the product with the highest share in firm's total sales at a given time.

[6]Utar (2014) shows some partial evidence of product churning in Danish Textile&Clothing (T&C) firms facing the removal of quotas on Chinese imports of T&C products in 2002.

[7]For instance, Dang (2017) investigates to what extent Vietnamese manufacturing firms have been incited to introduce product innovations following the increase in Chinese imports. He shows that contrary to what has been found for the U.S. by Bloom et al. (2016), there is no systematic evidence that rising imports from China make Vietnamese domestic firms adopt new technologies or innovations in their products.

have shown that firms' export performances as well as their decisions to start and stop exporting some products were impacted by how those products were embedded in their local environment (see Poncet and Starosta de Waldemar (2015) for evidence on China and Hazir et al. (2019) for evidence on France). These two previous studies rely on the so called methodology of product space developed by Hidalgo et al. (2007) to assess to what extent a product is embedded into its local environment. This methodology has been extensively used in the recent literature on related diversification. In particular, 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 link the product relatedness measure with regional comparative advantages and examine its impact on the growth path at the regional level (Boschma et al., 2012) or at the firm level, as the two studies cited above. In this study, we push this research avenue by relying on the product-space methodology to investigate to what extent local product relatedness matters in driving product downsizing and dropping by plants.

Second, another strand of the economic geography literature emphasizes that the spatial organization of the firm is not random and that firms, especially multi-plant ones, face complex location trade-offs related to the use of both internal and external resources (Woo et al. (2019), Alcácer and Delgado (2016), Behrens and Sharunova (2015)). In particular, Behrens and Sharunova (2015) argue that because interacting at a distance is costly, multi-plant firms should be geographically compact, and also that plants belonging to multi-plants firms should depend less on external agglomeration benefits than comparable standalone plants. Dissecting the micro-geographic location patterns of Canadian plants, they find robust evidence for the predictions that multi-plant firms are compact and their plants locate in areas offering potentially less external agglomeration benefits.

Finally, closer to our research question, a recent paper by Behrens et al. (2019) assesses the role played by geographical clusters in the resilience of Textile and Clothing (T&C) plants in Canada following the end of the Multi Fibre Arrangement (MFA) in 2000 and the consecutive rise of Chinese imports to Canada. Interestingly, Behrens et al. (2019) find that while being in a cluster didn't make Canadian T&C plants more resilient to China import competition, it made those plants more likely to switch into different industries following the end of the MFA. Their results suggest that the local environment might matter in more complex ways than one could *a priori* think of. Related to this line of inquiry, our paper provides broader evidence on how local product spaces are impacting product churning within Japanese manufacturing plants facing China import competition in a large variety of industries.

4 Data

4.1 Data sources

Our primary data are the longitudinal data sets of the Census of Manufacturers (COM). The COM is a comprehensive plant-level data set compiled by the Ministry of Economy, Trade, and Industry (METI). It covers all manufacturing plants with four or more employees located in Japan. It represents 57% of employment and 74% of sales in the System of National Accounts.

The COM provides information both at the plant and plant-product level. The plant level information covers location, the number of employees, the amount of tangible assets, the value of shipments and the sector classification at 4-digit level[8]. For each plant it also includes a unique firm identification code, which permits together with the location information to classify plants with respect to the (spatial) organization of the parent firm as shall be explained in the next subsection[9]. Whereas the plant-product level information refers to plant-product level shipments at the 6-digit level commodity classification. In this study, we use the plant-product level data over the period from 1997 to 2014.

In addition to the COM, we use trade data from Japanese customs to obtain information on China import competition. The customs data provides information on the value of exports from Japan by destination and the value of imports to Japan by country of origin at the HS 9-digit product classification. Since HS 9-digit classification is often revised, we use the concordance table of HS 9-digit codes constructed by Aoyagi and Ito (2019). Then, the concordant HS 9-digit import data are matched with the product codes in the COM, which is at the 6-digit. This matching is done by using the concordance table between the COM 6-digit commodity data and HS 9-digit trade data constructed in Baek et al. (2019)[10]. In our matched data set, 1125 products are included, while in the original data set in the COM, there are 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 can be matched with trade statistics (e.g., miscellaneous office paper products).

Lastly, we use the BACI database, which is maintained by CEPII research center and provides information on bilateral trade flows among countries at HS 6-digit level. We use this database to build the instruments for the import competition variable. We also use it in an intermediate step while we quantify the variables that account for the effect of agglomeration economies as shall be explained in Section 5.1.

[8]The information on the international trade activities at plant-level is quite limited. It provides the share of export revenue in total shipment from 2001. However, there is no information on the import side.

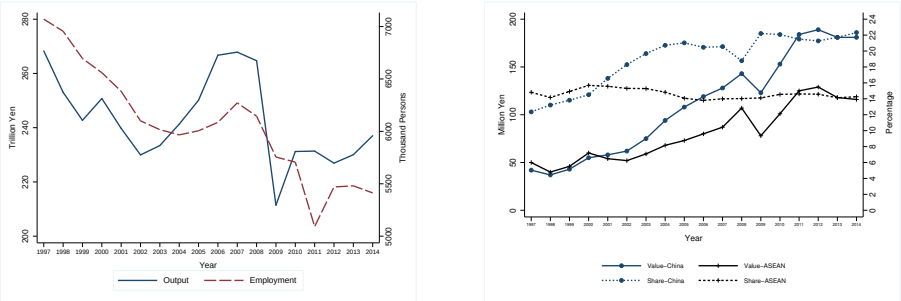
[9]Although the unique firm identification codes permit aggregating the plant-level data to firm-level, we refrain from running our estimations at the firm level because the aggregation leads to underestimation of firm characteristics. Our data covers only manufacturing plants, excludes stand-alone headquarters and R&D facilities, and thus does not give the whole picture of the firm.

[10]The concordance table is provided by Dr. Youngming Baek.

To define the spatial structure of the plant's organization, as well as to compute the variables related to agglomeration economies, we work at the level of the commuting zone. Commuting zones represent an intermediate spatial scale between prefectures and municipalities. The choice for commuting zones against prefectures is driven by the the fact that there are 47 prefectures in Japan, each comprises more than one local market, and thus they are too large to represent local markets as a geographical unit. Whereas, the choice against municipalities (*Shi Ku Cho Son*) is motivated by the fact that they are too small to cover local markets given that as of year 2005 there are 2500 municipalities in Japan. In contrast, the commuting zones represent local markets and they are constructed by merging several municipalities based on commuting patterns. We obtain the information on the 110 commuting zones from Minrokyu 2015 compiled by Asahi Shimbunsha[11].

4.2 Key figures

Our period of investigation is a period of contraction in the Manufacturing sector, and a period of expansion in China import pressure in Japan as illustrated by Figure 2. Between 1997 and 2014, manufacturing employment declined by about 23%. Manufacturing output has been more cyclical, but the general trend is also downwards over the period. Meanwhile, imports of Japan from China has more than doubled and the share of China in total imports of Japan has risen from 12% to 22%.



(a) Manufacturing employment and output

(b) Imports from China and ASEAN countries

Figure 2: Key Trends in Manufacturing and Imports in Japan (1997-2014)

In terms of the number of manufacturing plants, according to the first column of Table 1 there is also a decline (38.5 %) from 195,168 to 120,945. The remaining columns of Table 1 present the breakdown of plants with respect to corporate affiliation and plant product scope for 4 reference years during 1997-2014. This breakdown reveals that the shares of plants affiliated

[11]While there is no official definition for the commuting zones in Japan, several researchers propose slightly different definitions. For example, Kanemoto and Ishioka (2002) define the urban employment area, which does not cover all the municipalities in rural areas unlike the definition in Minryoku. The commuting zones in Minryoku are used in earlier papers such as Yano et al. (2003).

to single-plant and multi-plant firms have remained stable over time, and the former accounts for more than 85% of all plants. The shares of mono- and multi-product plants have also been stable over our period of investigation with the former accounting for about 75% of all plants. Interestingly, this stability contrasts with the finding by Bernard and Okubo (2016) according to which the share of Japanese manufacturing multi-product firms (not plants) increases over the period 1992-2006. However, both findings can be reconciled in so far as the expansion of multi-product firms partly occurs through the expansion of mono-product plants within multi-plant firms. Below, we show some evidence supporting this view[12].

Table 1: Breakdown of plants by corporate organization structure and product scope

		Breakdown of plants (as %)					
		owned by Single-plant Firms			owned by Multi-plant Firms		
Year	**Count**	Mono-product	Multi-product	Total	Mono-product	Multi-product	Total
1997	195 178	62.6	23.5	86.1	9.4	4.5	13.9
2002	168 563	64.2	23.5	87.7	8.3	4.1	12.3
2007	151 506	63.5	23.6	87.2	8.7	4.1	12.8
2014	121 042	61.4	24.7	86.1	9.4	4.5	13.9

Source: A matched database of Census of Manufacturers with International Trade data.

In Table 2, we distinguish plants owned by multi-plant firms further by considering the spatial organization of the parent firm. We label parent multi-plant firms that have all their plants in the same commuting zone as compact multi-plant firms referring to their compact spatial organization. Then, multi-plant firms that have their plants in different commuting zones are labeled as dispersed multi-plant firms owing to dispersion in their spatial organization. The table shows that the share of plants belonging to dispersed multi-plant firms has increased over time, and the increase is driven by mono-product plants, which represent the majority of affiliated plants. This implies that in a context of global decline in the number of Japanese manufacturing plants, there is a survival bias in favor of mono-product plants belonging to dispersed multi-plant firms.

In order to highlight plant heterogeneity among different types of corporate structure, we present some descriptive statistics on the average size of plants owned by single-plant, multi-plant, and dispersed multi-plant firms in Table 3. We report the average number of employees for mono-product plants, whereas we report both the average number of employees and the average number or products for multi-product plants.

This breakdown highlights large size gaps between our different plant categories. To illustrate, the average size of mono-product standalone plants is less than one-tenth of the average size of multi-product plants owned by

[12]Overall, these contrasting features of micro-data at firm versus plant levels show the importance of going deep into micro-data to reveal all the dimensions of the structural change that takes place within Manufacturing in high wage countries (see Fort et al. (2018) for a similar argument)

Table 2: Breakdown of plants by parent firm spatial scope

		Breakdown of plants (as %)					
		owned by Compact Multi-plant Firms			owned by Dispersed Multi-plant Firms		
Year	**Count**	Mono-product	Multi-product	Total	Mono-product	Multi-product	Total
1997	27 179	29.1	12.0	41.2	38.2	20.6	58.8
2002	20 806	25.9	10.7	36.6	41.1	22.3	63.4
2007	19 455	25.6	10.6	36.1	42.5	21.4	63.9
2014	16 836	24.0	9.9	33.9	43.8	22.3	66.1

Source: A matched database of Census of Manufacturers with International Trade data.

Table 3: Plant heterogeneity according to product scope and corporate organization structure

	Average # of employees	**Average # of products**
Mono-product plants *owned by*		
Single-plant firms	21	-
Compact Multi-plant firms	56	-
Dispersed Multi-plant firms	105	-
Multi-product plants *owned by*		
Single-plant firms	33	2.47
Compact Multi-plant firms	115	2.65
Dispersed Multi-plant firms	289	3.01

Source: A matched database of Census of Manufacturers with International Trade data.

dispersed multi-plant firms. A clear size hierarchy also appears between plants owned by compact multi-plant firms and plants owned by dispersed multi-plant firms, the latter being at least twice as large as the former whatever their product scope. Finally, within multi-product plants, the product scope of plants owned by dispersed multi-plant firms is systematically larger than the product scope of plants owned by compact multi-plant firms, or by standalone plants.

5 Econometric Model and Estimation Issues

5.1 Model Specification and Variables

Let i be the plant, k be the product, and t be the year we observe the outcome. Our econometric model, which is given in Equation 1, explains the plant-product level outcome in a given year $y_{i,k,t}$ as a function of some time-variant explanatory variables that are lagged by an amount of s and some time-invariant plant-product and time effects. The time-variant explanatory variables include the China import competition in k, characteristics of i and characteristics of k that vary with the location of plant i, which we denote

with the index $r(i)$.

$$\begin{aligned} y_{i,k,t} &= \beta_1 IMP_{k,t-s} + \beta_2 Share_{i,k,t-s} + \beta_3 IMP_{k,t-s} * Share_{i,k,t-s} + \beta_4 X_{i,t-s} \\ &\quad + \beta_5 LPA_{k,r(i),t-s} + \beta_6 LPR_{k,r(i),t-s} + \mu_{i,k} + \lambda_t + \epsilon_{i,k,t} \end{aligned} \tag{1}$$

where $\mu_{i,k}$, λ_t, and $\epsilon_{i,k,t}$ stand for plant-product fixed effects, year fixed effects, and the error term, respectively.

In this equation, the dependent variable indicates either product exit or product sales. When $y_{i,k,t}$ indicates a product exit, following Iacovone et al. (2013), it is defined as a dummy variable that takes the value 1 when plant i produces product k in year $t-s$ but not in t and onwards[13]. When $y_{i,k,t}$ indicates sales, it is defined as the logarithm of sales revenues of plant i in product k in year t, given that k was present in its product portfolio in year $t-s$.

Among explanatory variables, $IMP_{k,t-s}$ accounts for the China import competition pressure, and it is defined as the Chinese import share in year $t-s$ in Japan's total imports of product k[14]. $Share_{i,k,t-s}$ is defined as the share of product k in sales of plant i in year $t-s$. It allows to identify whether or not product k is a core product for plant i. In the literature on trade of multi-product firms (e.g., 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 for within-plant heterogeneity across products, we include the interaction term of $Share_{i,k,t-s}$ with the import competition measure, $IMP_{k,t-s}$.

$X_{i,t-s}$ is a vector of plant characteristics. It includes the labor productivity[15], the number of employees in logarithm, and the logarithm of the number of products at the plant-level.

Next covariates in the equation, $LPA_{k,r(i),t-s}$ and $LPR_{k,r(i),t-s}$, account for the effect of external agglomeration economies. These are product specific effects that vary with r(i), i.e, the location plant i. We define $r(i)$ as the commuting zone containing i as explained in Section 4.1.

Among these variables, local product alignment ($LPA_{k,r(i),t-s}$) is a dummy variable that controls for whether product k corresponds to a revealed comparative advantage (RCA) in the plant locality $r(i)$ at time $t-s$. Specifically, we first build output-based RCA indexes at the regional level as follows:

$$RCA_{k,r(i),t-s} = \frac{S_{k,r(i),t-s}}{\sum_k S_{k,r(i),t-s}} / \frac{\sum_{r(i)} S_{k,r(i),t-s}}{\sum_k \sum_{r(i)} S_{k,r(i),t-s}} \tag{2}$$

[13]For a few plants, we observed re-entry of a product after the plant has dropped it for a few years. In order to avoid treating each of these sways as exit, we consider it an exit and assign a value of 1 to our dependent variable when the product is dropped permanently until the end of our observation window.

[14]Following Iavocone et al. (2013) we use Japan's total imports of product k to scale this variable. An alternative would be to scale it using domestic consumption as an anonymous Referee has pointed out. However, it is not always easy to calculate domestic consumption because the difference between domestic production and exports become negative for some products at detailed level product classification.

[15]We do not compute total factor productivity (TFP) because information on the amount of tangible assets is restricted to plants with 30 or more employees.

where $S_{k,r(i),t-s}$ is the sales of product k produced in locality $r(i)$ at time $t-s$. We aggregate the product-level data in the COM to the commuting zone-level to calculate this variable. We then define the local product alignment dummy variable for each product k produced in area r(i) at time t-s, as follows:

$$LPA_{k,r(i),t-s} = \begin{cases} 1 & if RCA_{k,r(i),t-s} > 1 \\ 0 & otherwise \end{cases} \tag{3}$$

Local product relatedness ($LPR_{k,r(i),t-s}$) rests on the idea of a local product network, where nodes of the network are products produced in the locality and ties represent the proximity between products in terms of sharing common or complementary capabilities. Under this conception, agglomeration economies arising from core products of the locality is expected to be higher for products that are more proximate to these core products. Then, $LPR_{k,r(i),t-s}$ measures the density of ties from k to core products of the locality in all ties connecting k to the rest of the network. To quantify this variable we follow two steps.

The first step refers to quantifying the proximity between any pair of products and representing the local product network. We use the methodology of Hidalgo et al. (2007) to measure the bilateral product proximity. In this methodology, it is considered that if two products rely on common or complementary capabilities, which can be production factors, skills, knowledge base, institutions, business networks, etc., countries having a RCA in one are likely to export the other with RCA. Thus, we use Equation 2 once again, but this time to compute export-based RCA indexes at the country level. This means that in the equation we replace the index $r(i)$ with n, and $S_{k,n,t-s}$ becomes the value of exports of product k by country n at time $t-s$. We use the BACI data set prepared by CEPII to calculate the variable. Then, we calculate the conditional probability $P(k|j)$ that a country has RCA in product k given that it has RCA in product j:

$$P(k|j) = \frac{\text{\# of countries with RCA in both k and j}}{\text{\# of countries with RCA in j}} \tag{4}$$

Based on this conditional probability, Hidalgo et al. (2007) define the proximity between product k and j as $\phi_{kj} = min\{P(k|j),\ P(j|k)\}$. To illustrate, the proximity between Computer and TV&Radio is 0.264, while it is 0.05 for Bread and TV&Radio according to our calculations.

The second step refers to calculating the $LPR_{k,r(i),t-s}$, which shows how densely k is connected to core products of $r(i)$:

$$LPR_{k,r(i),t-s} = \left(\frac{\sum\limits_{j \neq k} \phi_{kj} LPA_{j,r(i),t-s}}{\sum\limits_{j \neq k} \phi_{kj}} \right) \tag{5}$$

We calculate the descriptive statistics and the correlation index on LPA and LPR for selected products, which is presented by Table 4.

Table 4: Descriptive statistics on LPA and LPR variables

	LPA				LPR				
	Mean	Sd	Min	Max	Mean	Sd	Min	Max	Correlation
Bread	0,196	0,397	0,000	1,000	0,127	0,067	0,026	0,519	0,272
Suits	0,214	0,410	0,000	1,000	0,129	0,067	0,025	0,542	0,232
TV	0,051	0,219	0,000	1,000	0,114	0,065	0,018	0,505	0,202
PC	0,104	0,306	0,000	1,000	0,112	0,066	0,017	0,489	0,231
Car	0,087	0,282	0,000	1,000	0,119	0,066	0,020	0,506	0,246

Source: BACI database.

The mean value of LPA varies by product. Bread and suits have an average of about 0.2, while electronics and automobiles have lower averages, indicating that the plants producing these products are concentrated in certain locations. The mean of LPR does not vary by product, but there is a moderate positive correlation between LPR and LPA regardless of the product.

5.2 Estimation Issues

One of the main issues in estimation is a possible endogeneity bias that may arise if the demand shock in Japan affects both import from China to Japan and the domestic product sales. To account for that, we follow the identification strategy proposed by Autor et al. (2013), and use the shares of Chinese import to the U.S. and to Europe to instrument the import competition variable. These variables can be expected to be correlated with Japan's imports from China, because they would all get affected by a supply shock in China, such as an improvement of market access from China to developed countries, or productivity enhancement of Chinese firms. However, they are likely to be exogenous as the demand shock in Japan may not have any effect on the European and the U.S. imports from China. Therefore, these variables can be expected to work as valid instruments[16].

A second issue arises in estimation of product exit as in that case we have a binary response variable in the main stage with fixed effects and endogeneity. We estimate a linear probability model instead of a probit or a logit model for two main reasons. First, in the presence of fixed effects the Maximum Likelihood Estimators (MLE) are reported to be biased (Greene, 2004). Second, unlike MLE estimation the two-stage least squares estimation does not require the first stage equation to be fully specified and the joint distribution of first and second stage errors to be fully parametrized.

[16] As Autor et al. (2013) argue, for consumer products such as TV, computer, and mobile phones, the product demand shocks may correlate across high-income countries because common innovations in the advancement of information and communication technologies (ICT) may affect the product demand for ICT products in Japan as well as the one in other high-income countries. In this case, our IV may not be independent of the import from China to Japan and thus, the coefficient of the import from China may be underestimated. As a robustness checks we replicated Table 5 and 6 excluding PC, TV and mobile phones. And we confirmed main findings remained the same. The results are provided upon readers' requests.

Lastly, we estimate the baseline specifications first by distinguishing mono- and multi-product plants. Then, we discriminate the plants further with respect to the organization structure of the parent firm, and estimate the baseline model separately for the three sub-samples of standalone plants, plants owned by compact multi-plant firms and plants owned by dispersed multi-plant firms. This allows us to examine the potential heterogeneity within mono- and multi-product plants that can be induced by the structure and spatial organization of the firm.

6 Results

6.1 Baseline Results

Table 5 presents the estimation results for the baseline specification, which is given in Equation 1, for mono-product and multi-product plants and for two plant outcomes[17]. These outcomes are product exit, and product sales conditional on the survival of the product. In these estimations we choose a time lag s of 3 years so as to focus on the short-run adjustments while letting sufficient time for their effects to be effective on the outcomes we study. In the appendix, we provide the estimations given in Table 5 for $s \in \{1, 2, 3, 4, 5\}$ and discuss the sensitivity of the results in Section 6.3.

Table 5: A global view of product exit and product sales responses of mono- and multi-product plants ($s = 3$)

	Later Response ($s = 3$)			
	Exit		Sales in Survivors	
	Mono-product	Multi-product	Mono-product	Multi-product
IMP	0.607***	0.816***	-0.876***	-1.381***
	(0.136)	(0.114)	(0.232)	(0.276)
IMP * Share		-0.379***		0.161
		(0.0447)		(0.116)
Share		0.0376***		0.488***
		(0.0117)		(0.0328)
log # of products		-0.0112***		0.00973
		(0.00292)		(0.00862)
log employees	-0.129***	-0.118***	0.419***	0.354***
	(0.00415)	(0.00550)	(0.0102)	(0.0149)
labor productivity	-0.0518***	-0.0452***	0.198***	0.165***
	(0.00259)	(0.00318)	(0.00657)	(0.00707)
LPA	-0.00607*	-0.00208	0.00878**	0.0272***
	(0.00310)	(0.00253)	(0.00432)	(0.00453)
LPR	-0.134***	-0.194***	0.111*	0.0994*
	(0.0324)	(0.0244)	(0.0600)	(0.0563)
Observations	1,885,123	1,740,105	1,282,943	1,135,855
Hansen J	1.175	5.940	2.465	1.371
Hansen J_p	0.278	0.0513	0.116	0.504
Widstat	3212	1827	2484	1258

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

[17] We present only the results of the second stage of the instrumental variables estimation. The first stage regression results can be provided upon readers' request

According to Table 5, China import competition fostered product exit in both mono- and multi-product plants in Japan. The impact of China import competition can further be observed in product sales given that the product is maintained. Regarding the magnitudes of the effects of IMP, a 1% increase in IMP increases product exit probability by 0.6% for mono-product plants and by 0.8% for multi-product plants. Conditional on the survival of the product, it also decreases product sales by 0.9% in mono-product plants and by 1.4% in multi-product plants. Since the average IMP increases from 16% to 33% during our sample period, a three-year average change in IMP is 3% and it increases product exit probability by 1.8% for mono-product plants and by 2.4% for multi-product plants; and decreases product sales by 2.6% and by 4.2% for the respective plant types.

When we take a closer look at the response of multi-product plants, we observe that the coefficient estimates for the interaction term $IMP * Share$ are statistically significant and have the opposite sign of the import competition coefficient. This implies higher resilience of core products and it is a result in line with our theoretical priors (Bernard et al. (2011), Mayer et al. (2014)) and with the previous empirical findings by Iacovone et al. (2013). However, conditional on survival, no further evidence on the resilience of core products is found in terms of sales. This might be driven by the fact that core products are more likely to be maintained, thus a long time lag (s) implies less variation in sales share of maintained product lines. Table 9 supports this argument by showing evidence on the resilience of the core product only for $s = 1$ and $s = 2$ but not later on.

A second group of coefficient estimates in Table 5 supports the hypothesis that plant heterogeneity can mitigate the negative impact of import competition. Given China import competition pressure, we observe for both mono- and multi-product plants that the higher the plant productivity and size, the higher the probability that the product is maintained and the more the product sales. In the case of multi-product plants, the plant product range also deters exit in any given product possibly due to common or complementary resources among their products.However, once the product is maintained no evidence is found on further effect of product range on subsequent sales.

The last group of coefficient estimates in Table 5 shed some light on whether external agglomeration can help plants to mitigate the negative effects of import competition. We observe different roles played by alignment with local specialization (LPA) and relatedness to local specialization (LPR). While former increases product sales conditional on the survival of the product, the latter mainly decreases the probability that the plant maintains the product. We observe also that these global findings depend on the time lag (s) as we discuss in the Appendix and they hide heterogeneity with respect to the spatial organization of the parent firm as we present in the next subsection.

To sum up, the analysis we present above confirms that manufacturing plants in Japan adjusted to China import competition either by dropping or by downsizing their most exposed product lines. Moreover, it comforts the view that product survival and sales are also impacted by the individual

characteristics of the plant, and by different types of external agglomeration economies.

6.2 Extension with the structure and spatial organization of the parent firm

In the next regression step, we integrate the structure and spatial organization of the parent firm to the analysis. The main issue at stake is to assess whether the negative impact of import competition varies according to the type of the parent firm. We indeed expect the sensitivity to China competition to differ between standalone plants, and plants owned by multi-plant firms, as adjustment costs are likely to differ across these two categories of plants. Additionally, we expect the structure and spatial organization of the parent firm to alter the role of certain individual plant characteristics, as the impact of the latter might be alleviated by the presence or strength of agglomeration economies internal to firms. Finally, the effects of external agglomeration economies discussed above might also conceal substantial heterogeneity particularly if internal agglomeration economies partly substitute for external ones (Behrens and Sharunova, 2015).

Table 6 distinguishes exit response of plants according to the structure and spatial organization of the parent firm. The estimation results for subsamples confirm the negative impact of import competition on the survival of products for each category of plants. Although the coefficients are systematically higher for plants owned by multi-plant firms, those differences are not statistically significant[18]. So, plants owned by large multi-plant firms do not show higher tendency to drop exposed products, despite the fact that they could in theory more easily reallocate their resources across different uses. Interestingly, they don't show either higher resilience to import competition than standalone plants, although they could in theory benefit from large corporations' specific assets to resist foreign competition[19].

Considering the group of coefficients related to plant level characteristics, we do not see much heterogeneity across our different sub-samples of plants. Still, it appears that plant labor productivity matters more for standalone plants as compared to plants owned by multi-plants corporations. This result could be explained by the fact that standalone plants are more sensitive to their own efficiency than plants that can rely on assets internal to the firm they belong to. Also, for plants belonging to compact multi-plant firms, for which internal agglomeration economies can be assumed to prevail, we find that the plant product range does not hinder product exit. This is consistent with the idea that within-plant complementarities are less key for plants which are part of a larger corporation and these plants rather rely on cross-plant complementarities within that corporation.

The heterogeneity regarding the effect of external agglomeration on product exit is more substantial across our different categories of plants. First, the

[18] We tested the null hypotheses on the equality of IMP coefficients by computing the z-score with unstandardized coefficient estimates.

[19] It could be that the two effects are counterbalancing each other. However, our empirical framework does not allow to disentangle these two potential opposing forces.

global result for mono-product plants that LPA deters exit is indeed driven by standalone plants. This result suggests that mono-product plants, which do not benefit from a large corporate affiliation, tend to rely on external economies as a possible substitute for the lack of internal economies. Another plausible explanation is that mono-product plants belonging to multi-plants firms are likely to represent the case where the firm maximizes economies of scale in a mature product, for which the returns of agglomeration can be constant or even negative due to saturation on the local market, fierce competition, etc. (Potter and Watts, 2010). Second, the global result for mono-product plants that LPR hinders exit is indeed driven by cross-group differences. Standalone plants do not benefit from local product relatedness, possibly because they lack resources or cross-fertilization opportunities arising from within plant/firm variety. Finally, although it is weak, we find some evidence that mono-product plants belonging to multi-plants firms tend to exit from products related to the specialization of the locality. This is a puzzling result that echoes the complex relationship between agglomeration economies and resilience to competitive shocks found in Behrens et al. (2019)[20].

In Table 7, we study plant responses in terms of product sales by distinguishing them according to the structure and spatial organization of the parent firm. Our results reveal that, conditional on survival, mono-product plants belonging to dispersed multi-plant firms are more sensitive to China competition than other mono-product plants [21] Specifically, following the same reasoning as above, the magnitude of the impact of IMP on product sales for mono-product plants owned by multi-plant firms is a 2% decrease in product sales in a three-year horizon.

[20] Understanding those relationships better would require to investigate the exit cases accompanied with new product entry, because exit for these plants implies corporate restructuring and corporate resources can make product switching less costly for them as compared to standalone plants.

[21] The null hypotheses suggesting equality of the coefficient of IMP for plants belonging to dispersed multi-plant firms to that of standalone plants and plants belonging to compact multi-plant firms are rejected at 90% confidence level.

Table 6: Determinants of product exit for mono- and multi-product plants (s=3): breakdown by firm organization

	Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-product	Multi-product	Mono-product	Multi-product	Mono-product	Multi-product
IMP	0.572***	0.772***	0.518*	0.684***	0.793**	0.876***
	(0.128)	(0.125)	(0.280)	(0.148)	(0.375)	(0.109)
IMP * Share		-0.389***		-0.366***		-0.562***
		(0.0442)		(0.117)		(0.0862)
Share		0.0468***		0.0330		0.0233
		(0.0123)		(0.0287)		(0.0199)
log # of products		-0.0133***		-0.00632		-0.0323***
		(0.00300)		(0.0119)		(0.00824)
log employees	-0.133***	-0.116***	-0.0920***	-0.0950***	-0.115***	-0.131***
	(0.00435)	(0.00635)	(0.00857)	(0.00757)	(0.00982)	(0.00631)
labor productivity	-0.0544***	-0.0472***	-0.0189***	-0.0249***	-0.0326***	-0.0286***
	(0.00286)	(0.00345)	(0.00445)	(0.00515)	(0.00432)	(0.00354)
LPA	-0.00734**	2.58e-05	0.00272	-0.0156**	-0.000443	-0.0151***
	(0.00333)	(0.00273)	(0.00880)	(0.00736)	(0.00526)	(0.00442)
LPR	0.00436	-0.100***	-0.0277	0.0755	0.268*	0.169***
	(0.0379)	(0.0369)	(0.134)	(0.117)	(0.143)	(0.0640)
Observations	1,659,743	1,431,356	85,497	90,743	129,507	205,177
Hansen J	0.989	6.888	0.0236	3.741	2.515	2.496
Hansen J_p	0.320	0.0319	0.878	0.154	0.113	0.287
Widstat	3089	1429	87.24	77.60	112.3	271.8

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 7: Determinants of product sales for mono- and multi-product plants (s=3): breakdown by firm organization

	Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-product	Multi-product	Mono-product	Multi-product	Mono-product	Multi-product
IMP	-0.742***	-1.249***	-0.671**	-1.795***	-1.995***	-1.744***
	(0.208)	(0.310)	(0.327)	(0.486)	(0.676)	(0.279)
IMP * Share		0.154		0.392		0.557**
		(0.121)		(0.263)		(0.249)
Share		0.430***		0.505***		0.671***
		(0.0339)		(0.0896)		(0.0638)
log # of products		0.00966		0.0418		0.0338
		(0.00946)		(0.0359)		(0.0241)
log employees	0.424***	0.378***	0.340***	0.212***	0.353***	0.255***
	(0.00999)	(0.0169)	(0.0189)	(0.0260)	(0.0266)	(0.0197)
labor productivity	0.198***	0.168***	0.140***	0.128***	0.190***	0.118***
	(0.00685)	(0.00749)	(0.0164)	(0.0201)	(0.0159)	(0.0122)
LPA	0.00913**	0.0179***	0.000286	0.0127	0.0109	0.0785***
	(0.00412)	(0.00481)	(0.0135)	(0.0212)	(0.0137)	(0.0144)
LPR	-0.0996	0.0685	-0.0991	-0.0607	-0.223	-0.294
	(0.0674)	(0.0786)	(0.189)	(0.324)	(0.298)	(0.188)
Observations	1,115,217	912,301	60,981	61,591	99,511	153,003
Hansen J	2.275	1.551	1.596	0.912	1.698	4.825
Hansen J_p	0.131	0.461	0.206	0.634	0.193	0.0896
Widstat	2372	968	77.22	50.40	97.43	208.4

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Considering the impact of the regional variables, we find that the positive impact of local product alignement(LPA) on product sales is mainly driven by standalone plants. For plants belonging to compact multi-plant firms, finding no evidence on such an effect can be explained by internal agglomeration economies (Behrens and Sharunova, 2015; Alcácer and Delgado, 2016). Indeed, internal economies are likely to be less strong for plants belonging to spatially dispersed multi-plant firms as interacting at a distance is costly. This may explain why we find some evidence on LPA variable for this group of plants. Lastly, we find no statistical evidence on the effect of LPR on sales regardless of the sub-sample. This reveals that the mitigating effect of the LPR variable we observed for all plants (Table 5) was indeed driven by cross-group differences. This means that it is safer to conclude that, once the product survives, there is no further impact of LPR on product sales.

6.3 Robustness Checks

We studied the sensitivity of the above-presented results along several directions. First and as mentioned before, we estimated the baseline specification with different time lags. Then, we extended the baseline specification with further international trade measures such as the share of import from ASEAN member countries or the share of exports from Japan to China in the focal product market. We provide all the estimation results in the Appendix, but discuss them briefly below.

To study the robustness of the results with respect to the choice on s, we repeated the estimations given in Table 5 for $s \in \{1, 2, 3, 4, 5\}$ and report the results in Tables 8 and Table 9 in the Appendix. As we vary s, we permit different mechanisms of adjustments to generate the response. For instance, $s = 1$ can be too short for product exit decisions to become effective. It permits modest product innovations, but may still be too early to observe the effects of these innovations on sales. As s gets longer, adjustments comprise more substantial innovations and it becomes more likely that these adjustments become effective on the product outcomes we study. However, when s gets too long, two issues arise. First, log-run adjustments can get intermingled with short-run response. To illustrate, after coasting for a few years efficient plants can switch to another product, which implies that long run and short run effects of plant efficiency on exit can be opposite. In addition to that as s gets too large, it may not make sense to try explaining product level outcomes with the product landscape of the locality or core products of the plant s years before as these latter evolve in time. Table 8 and Table 9 can be interpreted in the same vein.

Three main conclusions can be derived from Tables 8 and Table 9. First, the hypotheses that import competition fosters product exit and negatively affects product sales is confirmed regardless of the time lag. However, the negative effect of import competition on product survival gets stronger in time, which is consistent with the idea that exit decisions entail costs and take time. Also, the evidence on the resilience of core products gets stronger in line with the idea that adjustments through innovation are likely to take time. Second, the roles of plant specific characteristics on both product exit

and product sales remain almost the same as we vary s. Third, the effects of local product alignment and relatedness change over time. For instance, we find evidence on the effect of local product alignment on product exit only for short lags, which might be due to changes in comparative advantage of the locality over time. Furthermore, we observe a sign change in the effect of local product alignment over time, possibly reflecting two adjustment mechanisms working indifferent time horizons in different directions: hindering exit via product improvements versus fostering exit via switching to a related product.

A second series of robustness checks consisted in extending our baseline model with further foreign trade variables. The results of these exercises are presented in the Appendix . First, we controlled for the share of import from 10 ASEAN member countries in the focal product market (ASEAN IMP), because Japan's imports from low-wage countries are not only from China (see Tables 10 and 11). This additional control is considered as an endogenous variable, and instrumented in the same way as the share of Chinese imports. The coefficient estimates of the additional variable turned out to be statistically insignificant, and the main findings that are discussed in the previous section remained unchanged.

Second, we controlled for the share of exports from Japan to China in the focal product market to control for the export opportunities. According to Dauth et al. (2014), who investigate the impact of Chinese imports on German local labor markets, export demand from China mitigates negative impacts of import competition and contributes to retaining manufacturing sectors in Germany. Since Japan's exports to China are as large as its imports from China, increased export opportunities may mitigate the negative impact of import competition pressures as in Germany. In the case of product exit, as can be observed from Table 12, we don't find evidence on such a mitigation effect. Controlling for export opportunities leaves the results on product exit unchanged[22]. In the case of product sales, we find some statistical evidence on a mitigation effect as shown in Table 13. Export opportunities can help mitigating the impacts of import competition for standalone plants and mono-product plants belonging to compact multi-plant firms. Controlling for export opportunities leaves again the results on product sales almost the same. Here, the only noticeable difference is that mono-product plants owned by compact multi-plant firms become insensitive to China competition. This change can be explained by the fact that mono-product plants operated by compact multi-plant firms are likely to be upstream plants providing highly specific or high quality input to other plants of the compact firm[23]. Thus, once we account for alleviation of the negative impact of import competition by export opportunities, we can ex-

[22]The coefficients of the export opportunity variables are either statistically insignificant or they have the opposite sign. The unexpected positive coefficient estimate might be pointing out to relocation rather than closure of a product line for plants belonging to dispersed multi-plant firms, yet it is baffling for mono-product plants belonging to standalone and compact firms.

[23]Behrens and Sharunova (2015) emphasize indeed that multi-plant compact firms are characterized by strong vertical linkages across their units.

pect to observe no further negative impact of import competition on these plants benefiting from within firm vertical linkages.

Finally, we considered a measure of imported inputs from China. Increases in cheaper and a larger variety of imported input from China may be beneficial for product survival, and product sales. To take account of this effect, we follow the previous literature (Acemoglu et al. (2016) and Iacovone et al. (2013) in particular) by using Japanese Input-Output tables and calculating Chinese import shares weighted with input-output coefficients[24]. Again, as presented in Table 14 and Table 15, coefficient estimates of the new variable turned out to be insignificant and our key results remained unchanged.

7 Concluding Remarks

This study examines how Japanese plants change their product portfolios in response to the surge of import from China. Using the comprehensive Japanese plant-product level panel data set, we examine the impact of import competition on plant's product downsizing and exit. On the broad picture, we found that China import competition pressure did affect product exit and product sales, and that depending on plant characteristics and external agglomeration economies, Japanese plants could mitigate this effect at different extents.

We also found that the structure and spatial organization of the parent firm alter plants' product churning behavior, and also alleviate the role played by external agglomeration economies. In particular, mono-product plants owned by large dispersed firms are more sensitive to China competition than the standalone plants, in the sense that conditional on survival, they are more likely to downsize the sales of their exposed products. Also, for plants belonging to geographically compact multi-plants firms, where internal agglomeration economies can be expected, complementarities arising from the product range of the local plant do not play a role in hindering exit as it is the case for other plants. Lastly, external agglomeration economies arising from alignment with and relatedness to the local specialization play a mitigating role mostly for standalone plants.

One extension of this study would be to investigate plant-product entry and especially to focus on switching decisions. Plants owned by compact and dispersed multi-plant firms are likely to have higher opportunities to replace a product instead of dropping it merely. Thus, switching per se as an outcome is complementary to understanding the adjustment process. Also, the direction of switching is an interesting open question that can contribute to better understanding the spatial dimension of the adjustment process, and

[24]We used the input coefficients 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.

evolution of regional comparative advantages as a result of external shocks.

From policy point of view, our findings point out that local public authorities should be aware of the differences among standalone local plants and affiliated plants in terms of their reliance on local capabilities and of their heterogeneous responses to import competition. On that respect, another promising extension would be to shift the focus from product level churning to plant survival and employment to investigate further to what extent the effect of import competition on regional economies are contingent on firm structure.

Appendix A

Table 8: Sensitivity of product exit response of mono-product and multi-product plants with respect to time lag (s)

	($s = 1$)		($s = 2$)		($s = 3$)		($s = 4$)		($s = 5$)	
	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod
IMP	0.377***	0.514***	0.506***	0.661***	0.607***	0.816***	0.618***	0.823***	0.623***	0.811***
	(0.0797)	(0.0600)	(0.109)	(0.0852)	(0.136)	(0.114)	(0.142)	(0.124)	(0.150)	(0.132)
IMP * Share		-0.266***		-0.309***		-0.379***		-0.353***		-0.322***
		(0.0268)		(0.0351)		(0.0447)		(0.0454)		(0.0449)
Share		0.0127*		0.0235**		0.0376***		0.0332***		0.0322***
		(0.00742)		(0.00941)		(0.0117)		(0.0120)		(0.0113)
log # of products		-0.00773***		-0.014***		-0.0112***		-0.0126***		-0.0124***
		(0.00177)		(0.00236)		(0.00292)		(0.00320)		(0.00324)
log employees	-0.0950***	-0.0942***	-0.111***	-0.106***	-0.129***	-0.118***	-0.123***	-0.109***	-0.114***	-0.0950***
	(0.00304)	(0.00283)	(0.00352)	(0.00426)	(0.00415)	(0.00550)	(0.00460)	(0.00601)	(0.00507)	(0.00620)
labor productivity	-0.0374***	-0.0326***	-0.0438***	-0.0380***	-0.0518***	-0.0452***	-0.0525***	-0.0472***	-0.0492***	-0.0433***
	(0.00163)	(0.00174)	(0.00222)	(0.00247)	(0.00259)	(0.00318)	(0.00270)	(0.00336)	(0.00276)	(0.00334)
LPA	-0.00320**	-0.00277*	-0.00515**	-0.00311	-0.00607*	-0.00208	-0.00505	-0.000823	-0.00529*	-0.00169
	(0.00146)	(0.00142)	(0.00233)	(0.00207)	(0.00310)	(0.00253)	(0.00318)	(0.00293)	(0.00304)	(0.00303)
LPR	-0.0231	-0.0714***	-0.104***	-0.144***	-0.134***	-0.194***	0.0654	0.0831**	0.134**	0.190***
	(0.0215)	(0.0161)	(0.0288)	(0.0213)	(0.0324)	(0.0244)	(0.0498)	(0.0410)	(0.0657)	(0.0634)
Observations	2,071,042	1,926,526	1,977,447	1,830,384	1,885,123	1,740,105	1,827,834	1,688,909	1,706,395	1,570,327
Hansen J	0.489	5.079	0.814	6.464	1.175	5.940	1.780	5.211	2,243	6.051
Hansen J_p	0.484	0.0789	0.367	0.0395	0.278	0.0513	0.182	0.0739	0.134	0.0485
Widstat	11.58	9.396	11.54	9.262	11.38	8.765	11.42	8.547	11.72	8.278

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 9: Sensitivity of product sales response of mono-product and multi-product plants with respect to time lag (s)

	($s = 1$)		($s = 2$)		($s = 3$)		($s = 4$)		($s = 5$)	
	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod	Mono-Prod	Multi-Prod
IMP	-0.785***	-1.301***	-0.878***	-1.410***	-0.876***	-1.381***	-0.797***	-1.299***	-0.778***	-1.230***
	(0.210)	(0.226)	(0.226)	(0.264)	(0.232)	(0.276)	(0.216)	(0.267)	(0.220)	(0.272)
IMP * Share		0.449***		0.329***		0.161		0.0527		-0.0161
		(0.125)		(0.116)		(0.116)		(0.106)		(0.109)
Share		1.389***		0.828***		0.488***		0.294***		0.110***
		(0.0433)		(0.0359)		(0.0328)		(0.0305)		(0.0295)
log # of products		0.0581***		0.0202**		0.00973		-0.00324		-0.0199**
		(0.00891)		(0.00916)		(0.00862)		(0.00946)		(0.00953)
log employees	0.711***	0.633***	0.539***	0.470***	0.419***	0.354***	0.327***	0.275***	0.240***	0.200***
	(0.00733)	(0.0123)	(0.00944)	(0.0141)	(0.0102)	(0.0149)	(0.0111)	(0.0147)	(0.0110)	(0.0143)
labor productivity	0.451***	0.362***	0.292***	0.237***	0.198***	0.165***	0.141***	0.117***	0.0776***	0.0665***
	(0.00676)	(0.00785)	(0.00699)	(0.00783)	(0.00657)	(0.00707)	(0.00628)	(0.00722)	(0.00628)	(0.00724)
LPA	0.0129***	0.0566***	0.00939**	0.0391***	0.00878**	0.0272***	0.00428	0.0241***	0.000101	0.0128**
	(0.00332)	(0.00491)	(0.00386)	(0.00472)	(0.00432)	(0.00453)	(0.00460)	(0.00544)	(0.00486)	(0.00563)
LPR	0.0548	0.0691	0.0602	0.0817	0.111*	0.0994*	-0.174*	-0.288*	-0.131	-0.225
	(0.0565)	(0.0479)	(0.0652)	(0.0526)	(0.0600)	(0.0563)	(0.0971)	(0.148)	(0.0981)	(0.155)
Observations	1,732,625	1,577,469	1,480,136	1,325,248	1,282,943	1,135,855	1,129,018	994,820	981,862	854,830
Hansen J	1.974	1.314	1.565	1.315	2.465	1.371	2.371	1.852	3.217	2.302
Hansen J_p	0.160	0.519	0.211	0.518	0.116	0.504	0.124	0.396	0.0729	0.316
Widstat	11.90	9.983	12.26	10.11	12.56	9.632	13.12	9.375	13.66	9.215

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 10: Product Exit (s=3): Controlling for the share of ASEAN countries in imports of Japan

	All Firms		Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product
IMP	0.562***	0.800***	0.541***	0.768***	0.520*	0.701***	0.752**	0.855***
	(0.156)	(0.130)	(0.149)	(0.145)	(0.306)	(0.158)	(0.383)	(0.110)
IMP * Share		-0.377***		-0.389***		-0.366***		-0.559***
		(0.0460)		(0.0470)		(0.118)		(0.0860)
Share		0.0372***		0.0467***		0.0330		0.0226
		(0.0118)		(0.0127)		(0.0289)		(0.0198)
ASEAN IMP	-0.189	-0.144	-0.0995	-0.0519	-0.0277	0.0305	-0.801	-0.257
	(0.471)	(0.517)	(0.475)	(0.595)	(0.516)	(0.352)	(0.750)	(0.336)
log # of products		-0.0114***		-0.0133***		-0.00617		-0.0328***
		(0.00293)		(0.00302)		(0.0119)		(0.00823)
log employees	-0.130***	-0.118***	-0.133***	-0.116***	-0.0920***	-0.0951***	-0.114***	-0.131***
	(0.00464)	(0.00542)	(0.00491)	(0.00634)	(0.00851)	(0.00762)	(0.0102)	(0.00621)
labor productivity	-0.0519***	-0.0451***	-0.0545***	-0.0471***	-0.0189***	-0.0250***	-0.0327***	-0.0282***
	(0.00281)	(0.00319)	(0.00310)	(0.00346)	(0.00445)	(0.00521)	(0.00434)	(0.00361)
LPA	-0.00586**	-0.00185	-0.00722**	0.000113	0.00275	-0.0157**	0.000496	-0.0148***
	(0.00296)	(0.00261)	(0.00318)	(0.00280)	(0.00881)	(0.00741)	(0.00513)	(0.00444)
LPR	-0.138***	-0.198***	0.00313	-0.102**	-0.0285	0.0787	0.280*	0.155**
	(0.0327)	(0.0303)	(0.0380)	(0.0412)	(0.136)	(0.119)	(0.150)	(0.0681)
Observations	1,885,103	1,740,002	1,659,724	1,431,293	85,497	90,734	129,506	205,145
Hansen J	1.576	6.586	1.898	7.397	0.213	6.020	1.454	2.185
Hansen J_p	0.455	0.0863	0.387	0.0603	0.899	0.111	0.483	0.535
Widstat	481.8	291.1	448.4	220.1	29.73	20.09	25.38	44.36

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 11: Product Sales (s=3): Controlling for the share of ASEAN countries in imports of Japan

	All Firms		Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product
IMP	-0.678***	-1.291***	-0.546***	-1.163***	-0.720**	-1.985***	-1.945**	-1.650***
	(0.226)	(0.293)	(0.200)	(0.325)	(0.336)	(0.659)	(0.820)	(0.294)
IMP * Share		0.159		0.149		0.365		0.564**
		(0.115)		(0.122)		(0.256)		(0.245)
Share		0.487***		0.430***		0.513***		0.672***
		(0.0320)		(0.0332)		(0.0881)		(0.0633)
ASEAN IMP	0.999	0.820	0.884	0.761	-0.223	-0.873	2.643	1.292
	(0.728)	(0.941)	(0.692)	(1.041)	(0.582)	(1.355)	(1.849)	(0.977)
log # of products		0.0106		0.00999		0.0387		0.0346
		(0.00889)		(0.00965)		(0.0368)		(0.0247)
log employees	0.423***	0.353***	0.428***	0.377***	0.341***	0.213***	0.349***	0.255***
	(0.0133)	(0.0147)	(0.0131)	(0.0170)	(0.0190)	(0.0263)	(0.0294)	(0.0202)
labor productivity	0.199***	0.164***	0.199***	0.168***	0.140***	0.131***	0.189***	0.117***
	(0.00724)	(0.00708)	(0.00743)	(0.00745)	(0.0164)	(0.0203)	(0.0168)	(0.0123)
LPA	0.00755*	0.0258***	0.00771*	0.0165***	0.000143	0.0151	0.0120	0.0770***
	(0.00399)	(0.00487)	(0.00398)	(0.00498)	(0.0136)	(0.0217)	(0.0149)	(0.0154)
LPR	0.129**	0.121*	-0.0937	0.0883	-0.111	-0.100	-0.317	-0.207
	(0.0654)	(0.0636)	(0.0665)	(0.0860)	(0.186)	(0.333)	(0.355)	(0.206)
Observations	1,282,935	1,135,776	1,115,210	912,260	60,981	61,585	99,510	152,970
Hansen J	1.890	0.613	2.282	0.580	1.643	1.173	0.498	3.372
Hansen J_p	0.389	0.894	0.319	0.901	0.440	0.760	0.780	0.338
Widstat	342.5	216.5	314.5	165	19.11	17.06	15.01	32.87

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 12: Product Exit (s=3): Controlling for export opportunities

	All Firms		Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product
IMP	0.661***	0.852***	0.635***	0.812***	0.527*	0.689***	0.768**	0.892***
	(0.147)	(0.116)	(0.137)	(0.126)	(0.290)	(0.145)	(0.361)	(0.109)
IMP * Share		-0.383***		-0.392***		-0.372***		-0.567***
		(0.0474)		(0.0467)		(0.118)		(0.0855)
Share		0.0380***		0.0471***		0.0336		0.0228
		(0.0121)		(0.0128)		(0.0288)		(0.0199)
Exp opportunity	0.227*	0.166	0.224*	0.127	0.466**	0.127	0.307	0.397***
	(0.129)	(0.105)	(0.133)	(0.107)	(0.195)	(0.167)	(0.214)	(0.115)
log # of products		-0.0110***		-0.0132***		-0.00622		-0.0290***
		(0.00292)		(0.00301)		(0.0119)		(0.00837)
log employees	-0.127***	-0.117***	-0.130***	-0.116***	-0.0906***	-0.0951***	-0.116***	-0.129***
	(0.00471)	(0.00554)	(0.00480)	(0.00646)	(0.00814)	(0.00758)	(0.00928)	(0.00606)
labor productivity	-0.0512***	-0.0451***	-0.0539***	-0.0471***	-0.0180***	-0.0250***	-0.0326***	-0.0283***
	(0.00250)	(0.00316)	(0.00278)	(0.00345)	(0.00454)	(0.00517)	(0.00426)	(0.00357)
LPA	-0.00590*	-0.00182	-0.00718*	0.000265	0.00229	-0.0159**	-0.000576	-0.0155***
	(0.00348)	(0.00252)	(0.00369)	(0.00272)	(0.00914)	(0.00738)	(0.00533)	(0.00442)
LPR	-0.131***	-0.186***	0.00389	-0.0933**	-0.0359	0.0739	0.280**	0.183***
	(0.0321)	(0.0242)	(0.0372)	(0.0362)	(0.134)	(0.118)	(0.137)	(0.0647)
Observations	1,885,123	1,740,105	1,659,743	1,431,356	85,497	90,743	129,507	205,177
Hansen J	1.813	5.987	1.630	6.623	1.747	7.431	3.250	2.551
Hansen J_p	0.404	0.112	0.443	0.0850	0.417	0.0594	0.197	0.466
Widstat	2853	2618	2799	2188	44.07	69.15	57.26	311.8

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 13: Product Sales (s=3): Controlling for export opportunities

	All Firms		Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product
IMP	-0.685***	-1.171***	-0.545***	-0.974***	-0.481	-1.608***	-1.841***	-1.703***
	(0.225)	(0.260)	(0.205)	(0.277)	(0.358)	(0.466)	(0.638)	(0.276)
IMP * Share		0.151		0.137		0.416		0.558**
		(0.110)		(0.111)		(0.259)		(0.250)
Share		0.487***		0.430***		0.498***		0.670***
		(0.0305)		(0.0306)		(0.0891)		(0.0636)
Exp opportunity	0.759***	0.644**	0.758***	0.726**	0.775***	0.446	0.0967	0.312
	(0.221)	(0.274)	(0.220)	(0.298)	(0.275)	(0.366)	(0.414)	(0.318)
log # of products		0.0111		0.0105		0.0416		0.0369
		(0.00877)		(0.00958)		(0.0358)		(0.0241)
log employees	0.428***	0.356***	0.433***	0.380***	0.344***	0.211***	0.354***	0.257***
	(0.0154)	(0.0149)	(0.0156)	(0.0169)	(0.0196)	(0.0258)	(0.0251)	(0.0196)
labor productivity	0.200***	0.165***	0.200***	0.169***	0.141***	0.127***	0.190***	0.119***
	(0.00743)	(0.00703)	(0.00758)	(0.00744)	(0.0166)	(0.0201)	(0.0156)	(0.0122)
LPA	0.00926**	0.0282***	0.00958**	0.0191***	0.000247	0.0133	0.0106	0.0781***
	(0.00391)	(0.00478)	(0.00380)	(0.00515)	(0.0134)	(0.0211)	(0.0132)	(0.0144)
LPR	0.127*	0.132**	-0.0974	0.111	-0.0805	-0.0478	-0.194	-0.279
	(0.0658)	(0.0553)	(0.0709)	(0.0780)	(0.193)	(0.323)	(0.296)	(0.187)
Observations	1,282,943	1,135,855	1,115,217	912,301	60,981	61,591	99,511	153,003
Hansen J	12.60	4.892	11.72	4.876	12.69	7.282	8.787	9.492
Hansen J_p	0.00184	0.180	0.00286	0.181	0.00175	0.0634	0.0124	0.0234
Widstat	2530	1887	2233	1545	38.54	42.06	49.47	238.5

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 14: Product Exit (s=3): Controlling for imported inputs from China

	All Firms		Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product
IMP	0.681***	0.823***	0.631***	0.747***	0.672**	0.661***	0.958**	0.903***
	(0.189)	(0.162)	(0.182)	(0.173)	(0.327)	(0.192)	(0.423)	(0.173)
IMP * Share		-0.383***		-0.391***		-0.370***		-0.596***
		(0.0468)		(0.0450)		(0.119)		(0.0982)
Share		0.0388***		0.0475***		0.0337		0.0306
		(0.0122)		(0.0126)		(0.0291)		(0.0221)
log # of products		-0.0109***		-0.0129***		-0.00524		-0.0321***
		(0.00291)		(0.00299)		(0.0119)		(0.00827)
log employees	-0.129***	-0.119***	-0.133***	-0.117***	-0.0912***	-0.0960***	-0.114***	-0.132***
	(0.00435)	(0.00549)	(0.00444)	(0.00631)	(0.00893)	(0.00759)	(0.00995)	(0.00652)
labor productivity	-0.0519***	-0.0456***	-0.0545***	-0.0474***	-0.0187***	-0.0258***	-0.0326***	-0.0290***
	(0.00271)	(0.00317)	(0.00296)	(0.00345)	(0.00454)	(0.00520)	(0.00444)	(0.00359)
imported inputs	0.407	0.323	0.462	0.412	0.189	0.484	0.374	0.586
	(0.692)	(0.469)	(0.739)	(0.492)	(0.582)	(0.492)	(0.645)	(0.493)
LPA	-0.00556*	-0.00185	-0.00684**	0.000205	0.00322	-0.0153**	6.30e-05	-0.0143***
	(0.00315)	(0.00253)	(0.00332)	(0.00272)	(0.00891)	(0.00737)	(0.00576)	(0.00445)
LPR	-0.128***	-0.189***	0.0149	-0.0944***	-0.00774	0.0916	0.295**	0.173***
	(0.0332)	(0.0241)	(0.0390)	(0.0362)	(0.135)	(0.118)	(0.141)	(0.0644)
Observations	1,885,123	1,740,105	1,659,743	1,431,356	85,497	90,743	129,507	205,177
Hansen J	4.649	7.710	4.726	9.230	5.548	4.560	2.969	6.053
Hansen J_p	0.0978	0.0524	0.0941	0.0264	0.0624	0.207	0.227	0.109
Widstat	1506	743.9	1404	545.5	50.64	44.17	72.36	153.6

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

Table 15: Product Sales (s=3): Controlling for imported inputs from China

	All Firms		Single-plant Firms		Compact Multi-plant Firms		Dispersed Multi-plant Firms	
	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product	Mono-Product	Multi-Product
IMP	-1.122***	-1.603***	-0.974***	-1.515***	-0.795**	-2.129***	-2.640***	-1.613***
	(0.279)	(0.348)	(0.256)	(0.400)	(0.358)	(0.569)	(0.778)	(0.422)
IMP * Share		0.170		0.163		0.390		0.656**
		(0.117)		(0.125)		(0.265)		(0.275)
Share		0.485***		0.427***		0.502***		0.656***
		(0.0333)		(0.0348)		(0.0894)		(0.0693)
log # of products		0.00992		0.0102		0.0461		0.0357
		(0.00874)		(0.00963)		(0.0364)		(0.0240)
log employees	0.417***	0.353***	0.422***	0.377***	0.338***	0.205***	0.342***	0.261***
	(0.0105)	(0.0146)	(0.0101)	(0.0167)	(0.0190)	(0.0258)	(0.0300)	(0.0200)
labor productivity	0.198***	0.164***	0.197***	0.168***	0.139***	0.123***	0.188***	0.120***
	(0.00663)	(0.00691)	(0.00689)	(0.00738)	(0.0164)	(0.0203)	(0.0167)	(0.0121)
imported inputs	0.980	0.737	0.950	1.130	0.663	2.366*	1.403	-1.865
	(0.757)	(1.017)	(0.778)	(1.177)	(0.546)	(1.415)	(0.903)	(1.167)
LPA	0.00931**	0.0275***	0.00957**	0.0181***	0.000626	0.0136	0.0133	0.0756***
	(0.00461)	(0.00461)	(0.00437)	(0.00491)	(0.0135)	(0.0215)	(0.0152)	(0.0147)
LPR	0.116*	0.0999*	-0.0984	0.0672	-0.103	0.00766	-0.307	-0.300
	(0.0620)	(0.0561)	(0.0694)	(0.0783)	(0.191)	(0.335)	(0.316)	(0.188)
Observations	1,282,943	1,135,855	1,115,217	912,301	60,981	61,591	99,511	153,003
Hansen J	8.020	5.590	9.158	6.960	2.346	1.833	2.078	5.662
Hansen J_p	0.0181	0.133	0.0103	0.0732	0.309	0.608	0.354	0.129
Widstat	1170	546	1081	385.8	45.62	30.47	61.07	130.1

Notes: IV estimation, Plant-Product and Year FE included, errors clustered at the Product level. ***, ** and * indicate the statistical significance at 1%, 5% and 10% respectively.

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