Competition, Productivity and Product Mix: The Effect of China on Mexican Plants*

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Abstract

We investigate the effect of the rise in product market competition, measured by the increase in Chinese exports to Mexico and the US, on the productivity of Mexican plants between 1994 and 2007. We use detailed panel data on Mexican manufacturers matched with trade data at the product level. Using quantity-based estimates of plant-level productivity, we identify the effect of increased foreign competition on Mexican plants. We find robust evidence of a heterogeneous effect, with foreign competition causing initially low-productivity plants to fall farther behind their peers. We focus on within-plant reallocation of output as an intermediate mechanism. All plants reallocate production towards existing higher revenue products increasing skewness of within-plant sales distribution, but along the extensive margin, both within and across plants, the selection mechanism in terms of product dropping and plant exit appears impaired. However, initially high-productivity plants experience a high degree of product churning in response to competition by introducing new products while their low-productivity peers maintain the status quo. Interesting differences also emerge in terms of the types of products being introduced with initially low-productivity plants substantially less likely to introduce products closer to their comparative advantage or with higher potential for productivity-enhancement, possibly contributing towards such plants' loss in productivity.

Keywords: productivity, competition, productivity divergence, product mix, within-plant allocation.

JEL Classification: D22, D24, F14, F61, L25.

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1 Introduction

Whether and how competition stimulates productivity are fundamental questions in economics.[1] We bring evidence to bear on these questions by examining Mexican firms faced with the spectacular rise of China as a competitive threat in their domestic and major export markets. We find that low-productivity Mexican plants suffer a loss in productivity due to the rise of China, leading to a divergence in productivity within industries. We find evidence that this effect is related to a lack of within-plant reallocation of resources leading to a limited extensive margin response among low-productivity plants.

The recent rise of China in the world economy is a major event in economic history.[2] The implications of China's rise have been studied in many spheres – local labour markets in the US (Autor et al., 2013), political economy outcomes (Autor et al., 2016; Caselli et al., 2019; 2021a), firms' market power (Caselli and Schiavo, 2020; Caselli et al., 2021b), firm innovation and productivity (Bloom et al., 2016; Dhyne et al., 2017), and social aspects such as marriage and fertility (Autor et al., 2019a; Keller and Utar, 2019) and environmental pollution and infant mortality (Bombardini and Li, 2020). However, with a few exceptions, these studies focus on developed economies, even though middle-income countries and their export market positions are under arguably the greatest direct threat from Chinese competition.[3]

Figure 1 illustrates the increase in competition facing Mexican producers. The figure plots the weighted average of product-level shares of US imports from China, weighted by the exports of both Mexico and the rest of the world to the US.[4] It shows that from 1994 to 2007, China's market share increased by nearly nine percentage points for the average product exported by Mexican producers, compared to less than five percentage points for

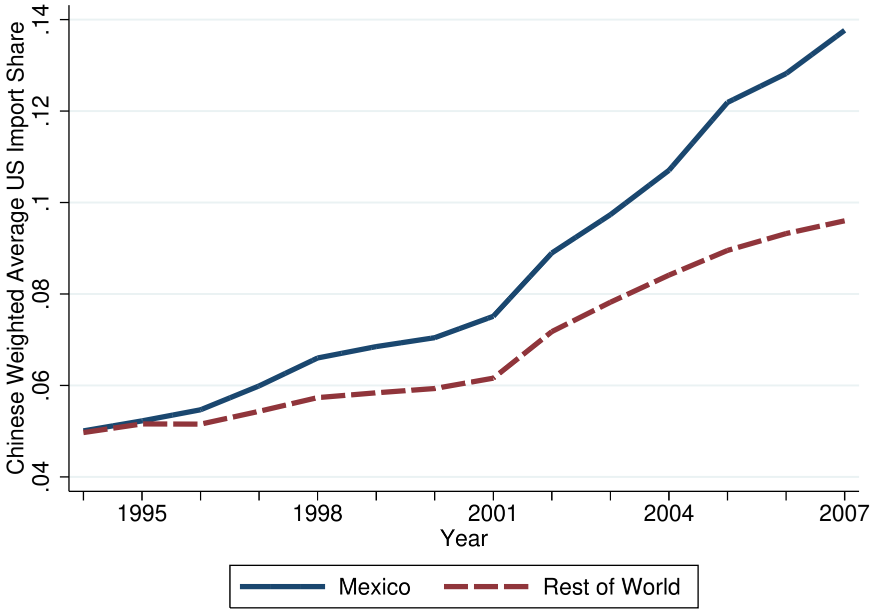
[1]Holmes and Schmitz (2010) review the history of this debate, including the contributions of major figures such as Schumpeter (1958), Stigler (1956), and Arrow (1962).

[2]Between 1990 and 2007, Chinese exports grew from 62 billion to 1.2 trillion United States dollars (USD), at the staggering average rate of about 20% per year. China became the world's largest exporter in 2009, and the second largest economy in the world in 2010. In terms of economic significance, this meteoric rise is possibly second only to the Global Financial Crisis and the Great Recession of 2008-09.

[3]Notable exceptions include Jenkins et al. (2008), Iacovone et al. (2013), and Utar and Torres Ruiz (2013).

[4]Trade data, by 6-digit Harmonized System product category, are from the UN Comtrade database.

Figure 1: Growing competition from China in the US Market



Notes: Weighted average import share calculated as the average Chinese share of product-level US imports, weighted by exports of Mexico (solid line) and all other countries (dashed line) to the US.

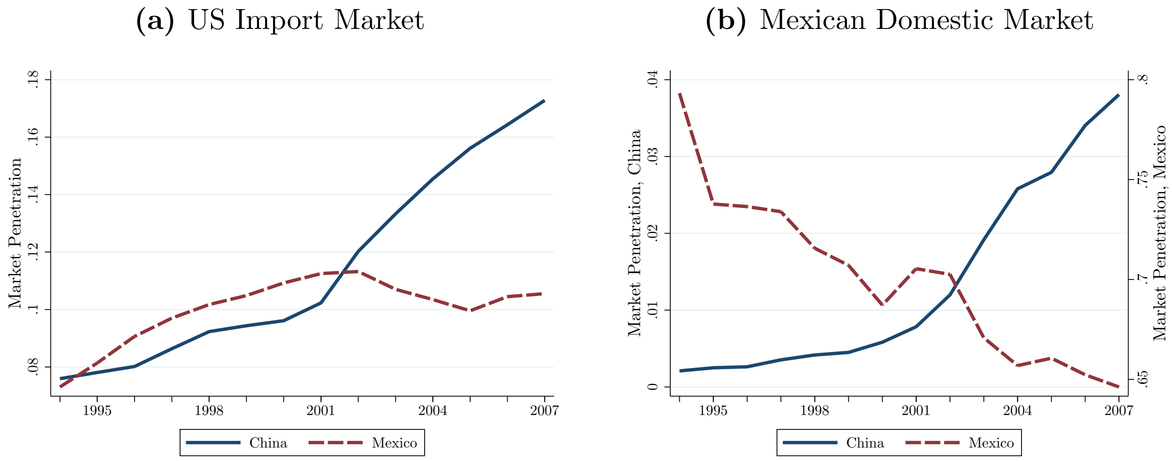
products exported by other countries. This indicates that, while many producers faced increased competition from Chinese exports over this period, Mexican producers were particularly exposed to the growth of Chinese export supply.

Figure 2 further illustrates the exposure of Mexican producers to increased competition from China. It shows that, over the same period, the market share of Chinese exports grew rapidly in the two largest markets for Mexican products – the US import market (Figure 2a) and Mexican domestic market (Figure 2b) – while market shares of Mexican producers were comparatively flat or falling. Together, these observations point toward a major rise in competition, which was particularly strong for Mexican producers, driven by supply-side factors in China.

What is the impact of such a large increase in exposure to foreign competition on the productivity of Mexican producers? To answer this question, we estimate the physical productivity of manufacturing plants in Mexico based on Ackerberg et al. (2015) and De Loecker et al. (2016).[5] We then estimate the causal effects of Chinese competition

[5]This is particularly relevant for our research question, as discussed in Backus (2020), since revenue

Figure 2: Market Penetration of China and Mexico



Notes: Market penetration in the Mexican domestic market calculated as a Mexican imports from China (blue line) and domestic sales (red line) as a share of total Mexican absorption in the tradable sectors (agriculture, mining and manufacturing). Absorption calculated using data from the OECD Structural Analysis (STAN) Database.

on productivity using variation in the growth of Chinese import shares across narrowly-defined products. To ensure that this variation is due to Chinese export supply shocks that are exogenous to local product-level shocks, we instrument for Chinese import shares using China's exports to other countries, similar to the approaches proposed by Autor et al. (2013) and Hummels et al. (2014). In addition, we control for pre-existing trends in line with the literature that makes of use of shift-share instrumental variables such as Borusyak et al. (2018) and Bombardini and Li (2020).

We find a non-linear effect of competition on productivity, with increased exposure to competition causing the productivity of initially less productive plants to decline relative to both more productive plants and those less exposed to competition. This result is robust to a battery of different specifications and controls, including IV quantile regressions (Powell and Wagner, 2014; Powell, 2016), which flexibly control for industry-by-year as well as plant and product fixed effects, and specifications allowing for lagged dependent variables to control for dynamics of the productivity process. The economic magnitude of the impact of Chinese competition on productivity is large. Plants at the 25th percentile of productivity experience a 5.2% decline in productivity due to one percentage point increase in Chinese market penetration, while plants at the 75th percentile see no

based productivity is contaminated by markups.

significant loss.

Guided by the rapidly growing literature on multi-product firms in trade, we explore how the Mexican plants in our data reallocate production within the plant in response to increased competition.[6] A common theoretical finding in this literature is that an increase in competition leads firms to cull their worst performing products and skew production toward higher-revenue products, increasing productivity by reallocating inputs toward lower-cost products. To explore this prediction in our setting, we estimate the effect of Chinese competition on several indicators of the within-plant composition of output. We find that all firms do indeed reallocate towards higher revenue products increasing skewness within existing products. However, when it comes to the extensive margin, surprisingly plants do not drop products as predicted by standard theory. This is also corroborated by the across-plant extensive margin response: rise in competition does not lead to a higher rate of exit of plants, in contrast to the well-known selection effect of Melitz (2003).[7]

A striking difference emerges though when investigating a different dimension of extensive margin. Initially low productivity plants are found to be significantly less likely to introduce new products with the rise in competition. This is especially true for less skill- or capital-intensive products or for products more intensive in machinery usage (relative to total capital). Rise in competition from China leads low-productivity plants to fewer options in expanding product scope in accordance with their inherent comparative advantage or products with more possibility for productivity enhancement through heavy machinery usage. Interestingly, many high-productivity plants increase their overall product scope in response to the increase in competitive pressure. By contrast, low-productivity plants do not respond significantly in terms of product scope. Such results are consistent with low-productivity plants' lack of response on introducing new products serving

[6]Important contributions in this literature include Eckel and Neary (2010), Bernard et al. (2011), Chatterjee et al. (2013), Dhingra (2013), and Mayer et al. (2014; 2016).

[7]The lack of product churning, as well as plant exit, among low-productivity plants potentially points towards costly adjustment, for example due to sunk costs of capital, which only more dynamic, larger plants are able to bear (e.g., Siegfried and Evans, 1994).

as a channel for their productivity lagging behind higher-productivity plants faced with increased competition from China.

Our data allow us to test for a number of alternative channels by which competition could affect productivity, such as export participation, investment and use of imported inputs. We find no statistically significant effect on these aspects of firms' behaviour that can explain the observed pattern of productivity response. We also check whether the distribution of the competition shock itself is different across different types of products or plants, and find no such evidence. Finally, we document that competition from China has the expected pro-competitive effects, inducing lower markups at the plant-product level with more pronounced effects on lower-performing products and less productive plants. This result points to the fact that the overall effect of greater competition is potentially nuanced.[8]

A large empirical literature estimates the effect of exposure to international trade on firm performance. In particular many papers examine the effect of trade liberalization episodes.[9] A robust finding is that firm productivity increases after trade liberalization. However, as De Loecker (2013) point out, these papers do not control for firm-level output and input prices and therefore do not identify the effect on physical productivity. De Loecker (2011a) introduces a demand system and structurally controls for unobserved output prices and finds a small positive effect of trade liberalization on the productivity of Slovenian firms. Bloom et al. (2016) apply the same methodology to twelve European countries and find that productivity, as well as measures of innovation, increased for textile firms after the elimination of quotas on Chinese imports. De Loecker et al. (2016) is the first to use data on output prices to estimate physical productivity without relying on an assumed demand structure and to control for unobserved input prices. They do not find a significant effect of reduced output tariffs on productivity.[10]

[8]These results are presented in detail in the appendix.

[9]Prominent examples include Pavcnik (2002), Schor (2004), Muendler (2004), Bernard et al. (2006), Amiti and Konings (2007), and Fernandes (2007).

[10]Similar to Amiti and Konings (2007) and Goldberg and Campa (2010), they do find a significant effect of reducing tariffs on inputs on plants' marginal costs.

Rather than relying on trade liberalization episodes, which often accompany other economic reforms and may affect exporters and non-exporters differently, we directly estimate the effect of increased Chinese competition on plant-level productivity in Mexico, capturing the effect of an external shock to competition in both domestic and foreign markets. In this regard, our paper is closely related to Autor et al. (2019b), who examine US manufacturing firms and find that patents and R&D expenditure decline in response to competition from China. Similar to our results, they find that the negative effect is stronger for less profitable and less capital-intensive firms. However, they do not consider the response of productivity, and their analysis is restricted to large, publicly-traded firms. Our paper is also closely related to Dhyne et al. (2017), who estimate the effect of import competition on the product-specific productivity of Belgian manufacturing firms. They find that increased competition, due both to worldwide supply shocks and the reduction in tariffs on Chinese imports, causes productivity to increase, especially for firms' top products. In connection to this literature, we make two novel contributions. First, we present causal evidence that competition from China lowers productivity among smaller, initially low-productivity plants leading to productivity divergence in a large, economically important middle-income country, which contrasts previous results based on developed countries. Second, we link the fall in productivity to the lack of extensive margin response in these plants, in contrast to the predictions of multi-product models of firm heterogeneity.

In addition, while previous studies focus on the response of innovation in developed countries, ours is the first to directly estimate the effect of Chinese competition on the productivity of manufacturers in a developing country, which is more likely to face head-to-head competition from Chinese producers. The channel we uncover, i.e., the within-plant reallocation of resources, is likely much more important for producers in less developed countries than the activities aimed at pushing the technological frontier, which are explored by Bloom et al. (2016) and Autor et al. (2019b). Related to this, while we find a non-linear effect of competition on productivity that, like in Autor et al. (2019b), is consistent with the predictions of Aghion et al. (2009), the fact that we focus on plants relatively far from the technological frontier means that it is likely that the effect that we observe is driven by a distinct mechanism.

The rest of the paper is organized as follows. Section 2 describes the data sources. Section 3 constructs our measure of foreign competition and shows how this measure has affected the value and quantity of sales of Mexican producers both in the export and domestic markets. The production function estimation is presented in Section 4. All main results are in Section 5. Section 6 presents some concluding remarks.

2 Data

We use plant-level data on manufacturing plants in Mexico. The data is detailed in Iacovone (2008) and Caselli et al. (2017), but we provide a brief description here. The data is collected from the *Instituto Nacional de Estadística y Geografía* (National Institute of Statistics and Geography, INEGI) and covers the period 1994-2007. We combine data from the *Encuesta Industrial Anual* (Annual Industrial Survey, EIA), the main survey covering the manufacturing sector, and the *Encuesta Industrial Mensual* (Monthly Industrial Survey, EIM), a monthly survey that monitors short-term trends.

The EIA draws from the industrial census and includes variables related to output indicators, inputs and investment. It contains information on 6,867 plants for 1994, with fewer in later years due to attrition, covering roughly 85 percent of all manufacturing output value. These data allow us to calculate the value of both domestic and imported raw material inputs, intermediate inputs, energy consumption, and capital investment. We use industry-level and aggregate price indices provided by INEGI to obtain real quantities of materials and investment, and we construct capital stocks using the investment series according the perpetual inventory method.

The EIM was run in parallel with the EIA, covering the same set of plants, and contains information on the number of workers, wage bills, and hours worked by occupation type (production or non-production). It also contains data on physical production, total sales, and export sales by product, based on a list of about 2,300 products across 205 six-digit activity classes provided by INEGI. This allows us to recover the value, quantity, and average unit prices of output by product and market (domestic or export) for each plant.

We combine the plant-level production and input data with product-level international trade data from the UN Comtrade database. Trade flows are classified according to the 6-digit Harmonized System (HS6, 1992 revision). The dataset contains information on value and weight of shipments for 5,129 product categories with positive US imports over our sample period. We manually matched the trade data with the production and input data at the product level based on product descriptions.[11]

3 The Foreign Competition Shock

To estimate the effect of foreign competition on the productivity of Mexican plants, we require an exogenous shock to product market competition. For this, we use product-level variation in the rapid rise of Chinese exports during the years of our sample. In this section, we define our measure of exposure to competition from China and show that a rise in competition from China had a significant effect on Mexican plants' sales.

3.1 Measuring Foreign Competition

We measure product market competition faced by Mexican plants from Chinese manufacturers as exposure to imports from China in a given product category (j) and market (k). Because the vast majority of Mexican exports go to the US, we consider two markets, the Mexican market and the US import market, $k \in \{M, U\}$.[12] Thus, we define the following

[11] We are indebted to Leonardo Iacovone and Ferdinand Rauch for providing their concordance between approximately 1,400 HS6 products and INEGI categories. By carefully matching product descriptions line-by-line, we were able to extend their concordance to map over 2,800 HS6 products to INEGI categories.

[12] Over our sample period, the US accounted for between 82% and 89% of Mexican exports.

two measures of market penetration:

$$\mathrm{MP}^{\mathrm{CH}}_{jMt} = M_{jCMt}/X_{jMt},$$

the share of Mexican expenditure (X) on product j that originates from China in year t, and

$$\mathrm{MP}^{\mathrm{CH}}_{jUt} = M_{jCUt}/M_{jUt},$$

the share of US imports (M) of j that originates from China in year t.

In all empirical specifications estimated at the product level, we control for plant-product or plant-product-market and year fixed effects. This implies that we identify the effect of Chinese product-market competition on Mexican plants based on the relative growth of Chinese market penetration net of any macroeconomic shocks and time-invariant product- and market-specific effects. After controlling for these effects, it is still possible that Chinese market share growth is correlated with product-level demand shocks, which would imply that $\mathrm{MP}^{\mathrm{CH}}_{jkt}$ is not purely a measure of exogenous competition from China. For example, if high US import demand causes new Chinese firms to enter the market, our estimates would likely be biased toward zero.

We control for potential correlation between $\mathrm{MP}^{\mathrm{CH}}_{jkt}$ and local product-level shocks in two ways. First, we use a one-year lag of Chinese market penetration, $\mathrm{MP}^{\mathrm{CH}}_{jk,t-1}$, to remove any contemporaneous correlation between $\mathrm{MP}^{\mathrm{CH}}_{jkt}$ and other product-level shocks. This also allows the estimation to pick up any effects that take time to materialize, as would be the case if the plants in our sample face adjustment frictions or make investments that take effect with a delay. Second, we instrument for $\mathrm{MP}^{\mathrm{CH}}_{jk,t-1}$ to control for any serial correlation between $\mathrm{MP}^{\mathrm{CH}}_{jk,t-1}$ and contemporaneous product-level shocks, for example, due to serially correlated demand shocks. In similar spirit to Autor et al. (2013), we instrument for $\mathrm{MP}^{\mathrm{CH}}_{jkt}$ using China's share of trade flows to destinations other than Mexico, the US, and Canada.[13] Like Autor et al. (2013) and others that have used a similar strategy,

[13]Several other papers have followed this approach using firm-level data, including Utar and Torres Ruiz

the identifying assumption is that the common component of variation in $\text{MP}^{\text{CH}}_{jk,t-1}$ and China's share of trade flows to other countries is driven by supply-side shocks to Chinese exports and not, for example, by correlated demand shocks across the set of importing countries.

We consider two instruments for $\text{MP}^{\text{CH}}_{jkt}$. The first (IV1) is the share of Chinese exports in total world trade, excluding Mexico, the US, and Canada, ($\text{MP}^{\text{CH}}_{jWt} = M_{jCWt}/M_{jWt}$). This instrument does not vary by market, which is consistent with Chinese competition driven by supply-side shocks to Chinese producers. However, we also consider a market-specific instrumental variable (IV2), which is equal to China's share of the imports of a set of middle-income Latin American countries for the Mexican market and high-income developed countries for the US import market.[14] Both instruments are valid under the condition that the correlation between $\text{MP}^{\text{CH}}_{jkt}$ and Chinese exports to third countries are driven by supply-side factors. IV2 will be the stronger instrument if the mix of product varieties within product categories that China exports varies with country characteristics, while we consider IV1 to be more conservative because it is robust to correlation of demand-side shocks across similar countries.

Productivity is measured at the plant level. To estimate the effect of competition on productivity, we aggregate our measure of Chinese competition over products and markets, using revenue shares in the first year available as weights:

$$\text{MP}^{\text{CH}}_{it} = \sum_{j}\sum_{k} \frac{X_{ijk,t_0}}{\sum_j \sum_k X_{ijk,t_0}} \text{MP}^{\text{CH}}_{jkt}.$$

The use of fixed weights avoids any potential simultaneity bias, for example due to a relationship between productivity and changes in a plant's product mix.

We purge our plant-level measure of Chinese competition of variation related to local

(2013), Dhyne et al. (2017), and Ciani and Mau (2018).

[14]We use all countries that meet the corresponding definition and have data available for the full sample period. For the IV2, these are (1) Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela for the Mexican market and (2) Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom for the US market.

shocks in the same way as for the product-level measure. First, we use a one-year lag of $\text{MP}_{it}^{\text{CH}}$ to remove any contemporaneous correlation with plant-level shocks. Second, we construct plant-level instruments for $\text{MP}_{it}^{\text{CH}}$ by aggregating our measures of China's share of trade flows to other countries using the same revenue share weights. This is broadly similar to the approach that Autor et al. (2013) use to construct and instrument for exposure of U.S. commuting zones to Chinese import growth. Goldsmith-Pinkham et al. (forthcoming) and Borusyak et al. (2018) provide conditions for the validity of shift-share instrumental variables such as this. Most relevant, in our panel data setting, Borusyak et al. (2018) show that our estimation of the effect of competition on plant-level productivity relies on essentially the same exclusion restrictions discussed above. Specifically, with fixed exposure weights and the inclusion of plant and year fixed effects, a sufficient condition for validity is that product-level changes in Chinese exports to other countries be uncorrelated with unobservable productivity shocks to plants with sales concentrated in those products, except those operating through the effect of increased competition.[15]

3.2 The Effect of Foreign Competition on Sales

Before estimating the effect of foreign competition on productivity, we examine the degree of increased competition Mexican producers faced due to the rise of Chinese exports. From the trade data alone, we can estimate the effect of foreign competition on Mexican exports. Using data on product-level trade flows from Mexico to the US, we estimate equations of the form

$$y_{jUt} = \beta^U \text{MP}_{jU,t-1}^{\text{CH}} + \gamma_j^U + \delta_t^U + \epsilon_{jt}^U, \tag{1}$$

where y_{jUt} represents the (logged) value or quantity of product-level Mexican exports to the US. Table 1 reports both OLS and IV results. In all specifications, an increase in

[15] The sufficiency result of Borusyak et al. (2018) also requires that average exposure to any one shock be sufficiently small, a condition easily satisfied in our setting where the vast majority of plants produce a small number of products and no single product accounts for a large share of aggregate revenue. See Bombardini and Li (2020) for a detailed discussion of the validity of the shift-share instrument.

Table 1: The Effect of Competition on Mexican Exports at the Product Level

Dependent variable:	Log Value			Log Quantity		
	OLS	IV1	IV2	OLS	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Market	-1.212^{***}	-3.958^{***}	-2.627^{***}	-1.198^{***}	-3.827^{***}	-2.521^{***}
Penetration	(0.177)	(0.707)	(0.678)	(0.195)	(0.768)	(0.740)
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,591	36,591	36,591	36,591	36,591	36,591
KP F-stat		248.1	254.4		248.1	254.4

Notes: *** denotes 1% significance. Standard errors in parentheses are clustered by HS6 product category.

Chinese market share is associated with a decline in Mexican exports. The coefficients estimates imply that a one percentage point increase the Chinese share of US imports results in drop in Mexican exports of between 1.2% and 4.0%. The instrumented specifications find larger effects, consistent with Chinese market share being positively correlated with US demand shocks.

Our matched plant and trade flow data allow us to expand the sample to include the Mexican domestic market and to estimate the effect of competition at the plant-product-market level. We estimate the effect of increased Chinese market penetration on Mexican plants' domestic and export sales, using specifications of the form

$$y_{ijkt} = \beta^s \mathrm{MP}^{\mathrm{CH}}_{jk,t-1} + \gamma^s_{ijk} + \delta^s_t + \epsilon^s_{ijkt}, \tag{2}$$

where y_{ijkt} is (logged) value or quantity of sales by plant i of product j in destination k at time t. The results, reported in Table 2, are very similar to those from the product-level trade data. We find that increased competition from China significantly reduced the sales of Mexican producers, and we again find that instrumenting for $\mathrm{MP}^{\mathrm{CH}}_{jkt}$ yields estimates that are larger in magnitude. The estimates imply that a one percentage point increase in Chinese market share results in as much as a 1.8% decline in a plant's output of the exposed product and a 2.4% decline in sales.[16]

[16]The fact that within-plant sales fall by more than output indicates that the Mexican producers also decrease their prices in response to increased competition, a pattern that may be obscured by compositional changes in the product-level trade data.

Table 2: The Effect of Competition on Mexican Plants' Sales at the Product-Market Level

Dependent variable:	Log Value			Log Quantity		
	OLS	IV1	IV2	OLS	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Market	-0.582^{***}	-2.407^{***}	-2.098^{***}	-0.457^{***}	-1.819^{***}	-1.547^{***}
Penetration	(0.124)	(0.385)	(0.410)	(0.130)	(0.365)	(0.405)
Plant-Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,579	100,579	100,527	100,579	100,579	100,527
KP F-stat		238.4	123.1		238.4	123.1

Notes: *** denotes 1% significance. Standard errors in parentheses are clustered by 8-digit INEGI product category.

Taken together, these results support our interpretation of $\text{MP}_{jkt}^{\text{CH}}$ as a measure of foreign product market competition that significantly affects Mexican manufacturers. They are also consistent with our intuition regarding the bias in OLS estimates. Interestingly, IV1 appears to be a stronger predictor of $\text{MP}_{jkt}^{\text{CH}}$, yielding greater first-stage F-statistics. Therefore, given that it is the more robust of the two instruments, we focus on estimates based on IV1 and consider OLS and IV2 only for robustness.

While it is clear that increased competition from China significantly reduced both the real output and sales of Mexican plants, such a negative effect of Chinese competition is neither surprising nor necessarily harmful for the overall Mexican economy. In particular, the overall effect of increased foreign competition could be positive it caused reductions in the levels and dispersion of markups, an increase in industry-level productivity through across-plant reallocation of resources as most models of selection and firm heterogeneity (e.g., Melitz, 2003) would predict, increases in plant-level productivity due to reallocation across products within plants (e.g., Mayer et al., 2014), or increases in productivity due to increased innovation or technology adoption. But does this increased competition indeed translate to productivity gain?

We estimate a quantity-based measure of plant-level TFP using a method based on De Loecker et al. (2016). This procedure estimates the production functions of multi-product plants, controlling for the well-known simultaneity and selection biases due to the dependence of plants' production and input decision on unobserved productivity as well as biases due the unobserved allocation of inputs within plants and unobserved plant-product-specific input prices. It also yields product-level estimates of markups and marginal costs for each plant, which we make use of in further corroborating the competition effects on the plants in our sample.

4 Productivity Estimation

Our data contain information on multi-product plants who sell their products in multiple destinations. We estimate the productivity of the plants in our data as in Caselli et al. (2017), which closely follows De Loecker et al. (2016). The latter extends the methodology of De Loecker and Warzynski (2012) to multi-product plants, which Caselli et al. (2017) further extend to a setting in which plants sell in multiple destinations. In this section, we present the important features of the estimation methodology for our application. For complete detail on the methodology, see Caselli et al. (2017) and De Loecker et al. (2016).

There are several advantages to this estimation framework for our purposes. First, it takes full advantage of the physical output data for each product and market for the plants in our data to estimate quantity-based productivity (TFPQ). By contrast, estimates of productivity based on revenue (TFPR) are known to be confounded with markups and demand shocks.[17] Because, unlike revenue, quantities of different products cannot simply be aggregated to the plant level, this requires a formal treatment of multi-product plants. Second, the estimation does not rely on assumptions regarding the form of demand or market structure faced by producers. This allows us to estimate the effect of foreign competition using variation across many industries that have very different demand-side features and competitive environments. Third, it places no restrictions on economies of scale or scope within plants, which allows us to empirically investigate channels of the effect of competition on productivity operating through the internal organization of plants.

[17]See, for example, Foster et al. (2008), De Loecker (2011b) and Garcia-Marin and Voigtländer (2019) for discussions of this phenomenon.

Our analysis is based on a general production function for plant i producing product j and selling in market k at time t:

$$Q_{ijkt} = F_j \left(V_{ijkt}, \boldsymbol{K}_{ijkt}; \boldsymbol{\beta}\right) \Omega_{it} e^{\epsilon_{ijkt}}, \tag{3}$$

where Q_{ijkt} is physical output, V_{ijkt} is a freely variable input (materials), $\boldsymbol{K}_{ijkt}$ is a vector of inputs (labor and capital) that face adjustment frictions, Ω_{it} is plant-level productivity, and ϵ_{ijkt} is an error term that captures unanticipated shocks to output and measurement error. We work with (3) in its log-linear form

$$q_{ijkt} = f_j \left(v_{ijkt}, \boldsymbol{k}_{ijkt}; \boldsymbol{\beta}\right) + \omega_{it} + \epsilon_{ijkt}, \tag{4}$$

where lowercase letters represent logged values. The key assumption is that the production function $f_j(\cdot)$ is common across producers of a specific product, which implies that output of a product differs across plants, destinations, and time periods as a result of differences in inputs, v_{ijkt} and $\boldsymbol{k}_{ijkt}$, and productivity ω_{it}. For estimation, we assume that f_j takes a flexible translog form.[18]

To recover an estimate of productivity, ω_{it}, we need to estimate the parameters of $f_j(\cdot)$.[19] De Loecker et al. (2016) delineate several causes of bias in these estimates. Because we observe physical output by plant, product, and market, our estimates do not suffer from the output price bias that is present in estimates based on revenue. Following Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2006), we control for the well-known simultaneity and selection biases due to unobserved productivity by assuming that ω_{it} follows a fourth-order Markov process and estimating its law of motion using standard moment conditions from the input control literature.

[18]The production function is given by $f_j(m_{ijkt}, l_{ijkt}, k_{ijkt}; \boldsymbol{\beta}) = \beta_m m_{ijkt} + \beta_l l_{ijkt} + \beta_k k_{ijkt} + \beta_{mm} m_{ijdt}^2 + \beta_{ll} l_{ijdt}^2 + \beta_{kk} k_{ijdt}^2 + \beta_{lk} l_{ijdt} k_{ijdt} + \beta_{lm} l_{ijdt} m_{ijdt} + \beta_{km} k_{ijdt} m_{ijdt} + \beta_{lkm} l_{ijdt} k_{ijdt} m_{ijdt}$.

[19]For single-product plants, given $\hat{\boldsymbol{\beta}}$, we recover ω_{it} directly from (4) using observed output purged of unanticipated shocks and measurement error ϵ_{ijkt}. For each multi-product plant producing J_{it} products in year t, we jointly recover ω_{it} and input allocations. Under the assumption that inputs can be allocated across products, we solve the system of $J_{it} + 1$ equations given by the J_{it} production functions and the restriction that product-level inputs sum to plant-level inputs.

The remaining biases arise because we do not observe (1) the allocation of inputs across products within a plant or (2) the prices of inputs at the plant-product level. We overcome the input allocation bias by using single-product plants to estimate the parameters of $f_j(\cdot)$. Because plants do not randomly select into producing a single product, we estimate a sample selection equation to control for selection bias. To control for input price bias, we include controls that proxy for output quality, based on the consistent theoretical and empirical finding in the literature that producers of higher quality products use higher cost inputs (e.g., Kugler and Verhoogen, 2012).

In our analysis of the effect of foreign competition on productivity, we explore several potential channels for this effect. It is worth emphasizing here that our productivity estimation places no restrictions on the relationship between productivity and the internal organization of the plant. While we impose that the form of $f_j(\cdot)$ is the same for single- and multi-product plants that produce the same product and that we can allocate input expenditures across products for multi-product plants, we allow ω_{it} to vary as plants change their use of inputs and their product mix. This is in contrast to theories of multi-product firms which specify such relationships and generate testable predictions. For example, Mayer et al. (2014) assume that a firm's marginal cost of producing each product is constant, which implies that producing relatively more of a low marginal cost product increases firm-level measured productivity. Instead, the structure underlying our estimation procedure makes no such predictions but allows for this and many other channels by which plants' productivity may depend on their responses to foreign competition.

An additional outcome of our estimation procedure is an estimate of the markup and marginal cost of each of a plant's products for each market. Under the assumption that plants may freely adjust their materials input, the first-order condition with respect to materials from a plant's cost minimization problem yields the following expression for the markup of product j in market k:

$$\mu_{ijkt} = \frac{\partial q_{ijkt}}{\partial m_{ijkt}} \frac{P_{ijkt} Q_{ijkt}}{W^m_{ijkt} M_{ijkt}} = \theta^m_{ijkt} \left(\alpha^m_{ijkt}\right)^{-1}, \tag{5}$$

where μ_{ijkt} is the markup, θ^m_{ijdt} is the output elasticity with respect to materials, and α^m_{ijkt} is the expenditure share of revenue spent on materials. Both of these objects are functions of the data and production function parameters that we estimate. Given markup estimates and data on prices, marginal costs can be recovered using the identity

$$mc_{ijkt} = \frac{P_{ijkt}}{\mu_{ijkt}}. \tag{6}$$

Table 3 provides summary statistics of the productivity estimates.[20] Panel A presents average productivity (demeaned by 6-digit industry and year) across quartiles of plant size, measured by total sales, number of workers, and capital stock. Consistent with typical theoretical and empirical findings in the literature, larger plants tend to be more productive. Panel A also shows that a products sold at higher markups are produced by more productive plants on average, and products produced at a lower marginal cost tend to be produced by more productive plants.

Panel B of Table 3 compares average productivity (demeaned by 2-digit sector and year) across industries sorted by different measures of intensity of competition. The first three columns employ commonly-used measures of market concentration, showing that the plants in less concentrated – i.e., more competitive – industries tend to be more productive, consistent with the selection mechanism present in standard heterogeneous firm models. The final column employs our measure of Chinese market penetration and shows that, similarly, plants in industries with a higher measure of foreign competition from China tend to be more productive. Thus, our productivity estimates produce similar patterns in the cross section as are commonly found in the literature. In what follows, we examine how a shock to foreign competition affects within-plant productivity over time.

[20] Summary statistics of the markup estimates are reported in the Appendix.

Table 3: Average productivity by plant and industry characteristics

Panel A: Plant and product type					
Quartile	Total sales	Workers	Capital	Markups	Marginal cost
1st quartile	-0.17	-0.13	-0.16	-0.09	0.69
2nd quartile	-0.07	-0.01	-0.00	-0.02	0.20
3rd quartile	0.11	0.05	0.02	-0.01	-0.21
4th quartile	0.15	0.10	0.17	0.13	-0.72

Panel B: Competition				Chinese
Quartile	CR5	HHI	Entropy	Mkt. Pen.
1st quartile	0.18	0.20	0.22	-0.21
2nd quartile	-0.01	0.04	-0.02	-0.35
3rd quartile	-0.09	-0.13	-0.10	0.02
4th quartile	-0.09	-0.11	-0.11	0.52

Notes: Panel A reports productivity (demeaned by 6-digit industry and year) by the quartile in which plants fall according to total sales, number of workers and quantity of capital, and plant-product-destination triplets fall according to their markups and marginal costs. Panel B reports productivity (demeaned by 2-digit sector and year) by the quartile in which plants fall according to three different measures of domestic competition, the concentration ratio of the top five plants (CR5, first column), the Herfindahl-Hirschman Index (HHI, second column) and the Entropy measure (third column), and the share of imports from China (fourth column). The table trims observations with markups that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets.

5 The Effect of Foreign Competition on Productivity

In this section, we identify the effect of foreign competition on productivity of Mexican plants by applying our measure of product market competition from Chinese manufacturers and instrumental variable strategy to our panel of plant-level productivity estimates. Importantly, we allow for heterogeneous effects across the productivity distribution.

5.1 Baseline Estimates

We allow for heterogeneous effects of competition across the productivity distribution in two ways. First, we estimate an equation of the form

$$\omega_{it} = \beta_1^p \mathrm{MP}_{i,t-1}^{\mathrm{CH}} + \beta_2^p \mathrm{MP}_{i,t-1}^{\mathrm{CH}} \times \mathrm{PROD}_{it} + \rho^p \mathrm{PROD}_{it} + \gamma_i^p + \delta_t^p + \epsilon_{it}, \tag{7}$$

where ω_{it} is the plant-level productivity, and PROD_{it} is an indicator for whether a plant's productivity is below the median within a sector and year. We control for both plant and year fixed effects. Thus, the β_1^p estimates the within-plant change in productivity due to increased foreign competition for a high-productivity plant relative to a high-productivity plant not directly exposed to increased competition, and β_2^p estimates additional effect for a low-productivity plant relative to an unexposed low-productivity plant.

Second, we use quantile regressions to flexibly identify heterogeneous effects of competition at different points in the productivity distribution. To maintain the same identification strategy and obtain coefficient estimates comparable to our fixed-effects IV estimates, we employ the quantile regression estimator of Powell (2016). Specifically, we estimate an equation of the form

$$\omega_{it} = \beta\left(u_{it}^{\star}\right) \mathrm{MP}_{i,t-1}^{\mathrm{CH}} + \delta_t\left(u_{it}^{\star}\right). \tag{8}$$

In this specification, $\beta(\tau)$ is the effect of competition on productivity for a plant in the τth quantile of the productivity distribution. The disturbance term $u_{it}^{\star} \sim U(0,1)$ represents unobserved (fixed and time-varying) characteristics that determine a plant's ranking in terms of productivity and is given by $u_{it}^{\star} = g\left(\gamma_i, u_{it}\right)$ for some unknown function $g(\cdot)$. Like our IV regressions with plant fixed effects, this estimator allows for arbitrary correlation between our instruments and the fixed effects (γ_i) and relies on within-plant variation to identify the effect of competition. Inclusion of additive year fixed effects, $\delta_t\left(u_{it}^{\star}\right)$, as in Powell and Wagner (2014), makes this specification comparable to (7) and implies that $\beta(\tau)$ is the effect of competition for a plant at the τth quantile of the productivity distribution of plants within a given year.

Our baseline empirical evidence of the effect of competition on productivity is presented in Table 4, based on equation (7). The first three columns present the estimates, which control for plant and year fixed effects. The instrumented specifications (columns 2-3) find that increased foreign competition causes a significant decrease in productivity for plants in the bottom half of the distribution. The estimates based on IV1 also find a significant positive effect of competition on productivity for more productive plants, but this result is not robust to the specification of our instrument. More robust is the conclusion that rise in competition due to emergence of China in the world market has

Table 4: China effect on productivity at the plant level

	FE	IV1	IV2	FE	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Mkt. Pen.	0.274	0.884**	0.810*	0.212	1.668*	1.446
× High Productivity (β_1^p)	(0.182)	(0.418)	(0.437)	(0.250)	(0.925)	(0.918)
Chinese Mkt. Pen.	-0.199	-1.661***	-1.171**	-0.657**	-2.667**	-2.144**
× Low Productivity ($\beta_1^p + \beta_2^p$)	(0.190)	(0.762)	(0.523)	(0.258)	(1.195)	(0.897)
Difference (β_2^p)	-0.473*	-2.545***	-1.981***	-0.869***	-4.335***	-3.591***
	(0.271)	(0.855)	(0.716)	(0.330)	(1.288)	(1.115)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No
Industry-Year FE	No	No	No	Yes	Yes	Yes
Observations	35,859	35,859	35,859	35,717	35,717	35,717
KP F-stat		35.48	64.18		45.51	77.05

Notes: *** denotes 1% significance, and ** denotes 5% significance. Standard errors in parentheses are clustered by plant. The dependent variable is the log of total factor productivity. All regressions include a dummy for low productivity (PROD) among the regressors.

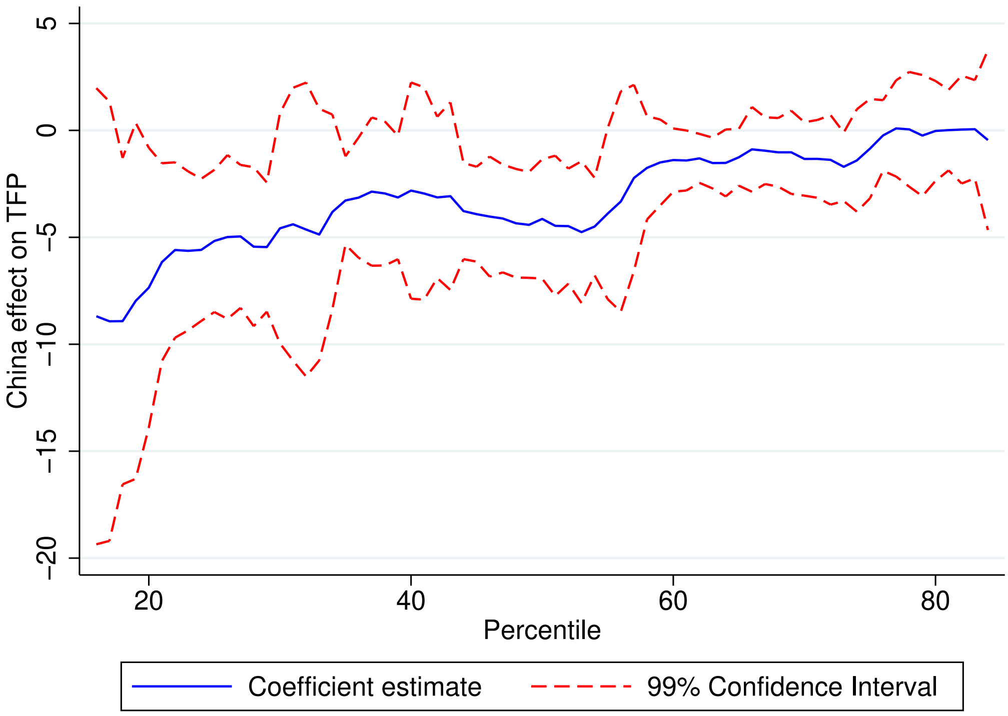
a divergent effect on the productivity of Mexican plants within narrowly defined industries.[21]

Stronger evidence of the impact of Chinese competition on productivity of Mexican plants is presented in columns 3-5 of Table 4, in which we additionally include industry-year fixed effects. This specification controls for any industry-specific trends. We find the same qualitative pattern, but the estimates are uniformly larger in magnitude. This indicates that Chinese competition tended to increase in industries in which there were pre-existing trends of productivity convergence. Based on our preferred instrument (IV1) and controlling of industry-specific trends, our estimates suggest that a one percentage point increase in Chinese market penetration induces a 2.7% relative decline in productivity for plants with below-median productivity – or a 4.3% decline in productivity relative to a high-productivity plant hit with the same shock.

Next, we document the impact of foreign competition on productivity of plants using quantile analysis. Figure 3 plots the coefficient estimates and 99% confidence intervals, based on IV1, for each percentile between the 15th and 85th, beyond which the precision

[21] As in our estimates of the effect of competition on sales, controlling for local shocks by instrumenting for $\mathrm{MP}_{it}^{\mathrm{CH}}$ leads to estimates of the effect of competition that are larger in magnitude, again indicating our instruments purge the Chinese market share variable of variation that is correlated with local shocks.

Figure 3: Quantile Regression Results



of the estimates falls considerably.[22] We again find that foreign competition leads to a significant reduction in productivity for plants below the median of the productivity distribution, relative to those not directly exposed to increased competition. For example, we find that a one percentage point increase in Chinese market penetration is associated with a 5.2% fall in productivity at 25th percentile of the productivity distribution. However, unlike the least squares regression results, we find no significant effect for plants at the top of the distribution. There is a clear monotonic relationship between productivity quantile and the estimated effect, with significant negative effects over most the range below the 55th percentile and insignificant effects for higher quantiles.[23]

We also consider a specification based on (7) that includes lagged plant-level productivity as an additional explanatory variable to control for dynamic effects that might be

[22]Coefficient estimates for each quartile based on both IV1 and IV2 are presented in the Appendix.

[23]A possible explanation for the linear regression finding of a significant positive effect of competition on productivity for the above-median plants, while the quantile regressions find no significant effect, is that quantile regression estimates are less affected by outliers, which suggests that the linear regression results are driven by a small number of firms in the top half of the productivity distribution.

correlated either with changes in our instrument or with our identifier of low-productivity plants. We use system GMM with a two-year lag of productivity as an instrument for lagged productivity to control for correlation between the lagged dependent variable and fixed effects. Table 9 in the Appendix reports the results. For the instrumented specifications, the effect of competition on high-productivity plants is no longer significant, while the negative effect on low-productivity plants is larger in magnitude though less precisely estimated.

In order to test whether our empirical results are driven by pre-existing trends, we conduct a placebo test on our baseline results of Table 4. In this exercise, we replace the right hand side measure of China shock at year t by the same measure 5 year ahead. In the absence of any pre-existing trend driving our results, we do not expect to see any significant effect of competition on productivity using this placebo measure. The results presented in Table 10 find some significant effects if we control for only year fixed effects. However, if we control for industry-year fixed effects as in columns 4-6, we fail to find any significant effect of competition on productivity in this placebo exercise. This confirms that our baseline evidence of the impact of competition on productivity, while controlling for industry-year fixed effects, is unlikely to be driven by pre-existing trends.

Taken together, our results imply that increased foreign competition is associated with a large and significant relative decline in productivity for Mexican plants below the median of the productivity distribution. This effect is robust across a number of specifications. The evidence for an effect of competition on the productivity of more productive plants is mixed. Across all specifications that we consider, most find a statistically insignificant or marginally significant positive effect. In all specifications, the difference between estimated effects on low- and high-productivity plants is large and highly significant. Thus, we conclude that increased competition from China caused a large and statistically significant divergence in productivity across plants in Mexico.

To put the magnitude of the effects that we estimate in context, consider our baseline estimates with the inclusion industry-year fixed effects (columns 5-6 of Table 4). China's average market penetration across the Mexican and US markets rose by 9 percentage points over our sample period. This implies that increased competition from Chinese exporters resulted in a 19%-24% loss of productivity for a typical low-productivity plant relative to an unaffected plant and a 32%-39% loss relative to a high-productivity plant hit by the same increase in competition.

Our findings contrast with the empirical evidence presented in Bloom et al. (2016) and Dhyne et al. (2017) who find a positive effect of Chinese competition on European firms.[24] The empirical evidence presented above contradicts standard theoretical prediction from heterogeneous firm models such as Melitz (2003) and Mayer et al. (2014). These models would predict that higher competition would lead stricter selection and hence higher average productivity for survivors, both at industry and at plant level. Backus (2020) also fail to find any significant effect of competition on selection. Our plant level empirical evidence contradicts the selection hypothesis and instead provides support for a type of U-shaped effect on productivity more in line with Aghion et al. (2005).[25]

In Aghion et al. (2005), U-shaped effect of competition on productivity arises via its effect on innovation, viz. frontier firms invest in innovation in order to escape competition whereas firms at the bottom of productivity distribution are further discouraged from innovating due to increased competition since it further limits possibility of ever catching up.[26] In the Mexican data, plant level information on innovation activities or R&D expenditure is quite patchy. Hence, we cannot directly test for the effects of increased Chinese competition on the innovation activities of firms. However, the reason models

[24]Along a similar line, Abeberese and Chen (2020) also find a positive effect of increase in competition induced by a fall in intranational trade costs on firm productivity.

[25]We also investigate several possible explanations for our baseline results other than a true differential effect of increased competition on plants' productivity. Our results could be driven by differential exit rates of plants in response to increased competition. The literature on intra-industry reallocation (e.g., Melitz, 2003) predicts that low-productivity plants are more likely to exit when faced with increased foreign competition. We would expect this mechanism to select low-productivity plants with higher expected growth and so work against the effects that we estimate. Regardless, we examine this possibility by estimating a specification identical to (7) but with an indicator for plant exit as the dependent variable. Table 14 reported in the Appendix presents the results. We do not find a significant effect of Chinese competition on exit for any plants. While this result is somewhat surprising in itself, it indicates that our main results are in no way driven by plant exit.

[26]Elewa (2019) presents a theory of multi-product firms with a similar non-monotonic relationship between competition and product scope.

like Melitz (2003) and MMO predict an improvement in plant-level productivity following increased competition is due to more efficient within-firm reallocation. Because our data contain detailed plant-product level quantity and sales information, we next examine whether the loss in productivity observed among initially low-productivity plants is due to the lack of a functioning selection mechanism across products within-plant.

5.2 Potential Channel: Within-Plant Reallocation

We investigate how plants reallocate production across products in response to competition from China. A number of models of heterogeneous multi-product firms predict that firm-level productivity increases in response to an increase in competition as plants adjust their product mix and reallocate production across products.[27] Though they differ in their assumptions regarding demand and market structure, these models make several consistent predictions. On the extensive margin, firms drop their lowest-performing products, with lower-productivity firms being more likely to drop products. On the intensive margin, output and sales fall by more for firms' lowest-performing products, increasing the skewness of output toward firms' "core" products.

To examine how the plants in our sample respond to competition along these dimensions, we consider several measures of the within-plant composition of production. First, we consider measures of the skewness of the distribution of plants' sales across products. Following Baldwin and Gu (2009) and Mayer et al. (2014), we measure skewness using Theil's entropy index, which is greater for plants whose sales are more concentrated in their top products. Cadot et al. (2010) show that the Theil index can be decomposed into between and within components that correspond to extensive and intensive margin

[27] See, for example, Eckel and Neary (2010), Bernard et al. (2011), Chatterjee et al. (2013), Dhingra (2013), and Mayer et al. (2014; 2016).

skewness measures:

$$
\begin{aligned}
T_{it}^{T} &= \sum_{j=1}^{N_{it}} \frac{x_{ijt}}{\sum_j x_{ijt}} \ln\left(\frac{x_{ijt}}{\sum_j x_{ijt}}\right) \\
&= \underbrace{-\ln(N_{it})}_{\text{Between}} + \underbrace{\frac{1}{N_{it}} \sum_{j=1}^{N_{it}} \frac{x_{ijt}}{\bar{x}_{it}} \ln\left(\frac{x_{ijt}}{\bar{x}_{it}}\right)}_{\text{Within}} \\
&\equiv T_{it}^{B} + T_{it}^{W},
\end{aligned}
$$

where N_{it} is the number of products produced by plant i (or, product scope), x_{ijt} is its total sales of product j, and $\bar{x}_{it} = (1/N_{it}) \sum_j x_{ijt}$. Clearly, T_{it}^{B} increases when products are dropped. Given N_{it}, T_{it}^{W} increases as sales become more skewed toward the plant's top products.[28]

As Bernard et al. (2010) show, it is common for plants to simultaneously drop and add products. To capture this phenomenon, we split T_{it}^{B} into separate components due to product adding and dropping. In terms of product scope, we can decompose T_{it}^{B} in the following way:

$$
\ln(N_{it}) = \ln(N_{i0}) + \ln(N_{it})^{+} - \ln(N_{it})^{-},
$$

where $\ln(N_{it})^{+}$ and $\ln(N_{it})^{-}$ are partial sum processes of positive and negative changes in $\ln(N_{it})$:

$$
\begin{aligned}
\ln(N_{it})^{+} &= \sum_t \Delta \ln(N_{it})^{+} = \sum_t \ln(N_{i,t-1} + N_{it}^{\text{Add}}) - \ln(N_{i,t-1}) \\
\ln(N_{it})^{-} &= \sum_t \Delta \ln(N_{it})^{-} = \sum_t \ln(N_{i,t} - N_{it}^{\text{Drop}}) - \ln(N_{i,t}),
\end{aligned}
$$

where N_{it}^{Add} and N_{it}^{Drop} are the number of new products added and existing products dropped between $t-1$ and t.[29]

[28] Mayer et al. (2014) implicity calculate T^{W} because they consider only the set of products that a firm exports to a given destination.

[29] The changes $\Delta \ln(N_{it})^{+}$ and $\Delta \ln(N_{it})^{-}$ are defined in this way to preserve the identity $\Delta \ln(N)_{it} = \Delta \ln(N)_{it}^{+} + \Delta \ln(N)_{it}^{-}$, given the asymmetry in $\ln(\cdot)$. This definition implicitly counts new product additions first and product drops second. Counting drops first produces similar results.

Table 5: China effect on intensive and extensive margins at the plant level

Dependent variable	T^W (1)	$\ln(N_{it})$ (2)	$\ln(N_{it})^+$ (3)	$\ln(N_{it})^-$ (4)
Chinese Mkt. Pen.	0.705***	1.906***	-1.316***	-3.222***
× High Productivity	(0.205)	(0.435)	(0.386)	(0.572)
Chinese Mkt. Pen.	0.453**	0.931***	-2.251***	-3.182***
× Low Productivity	(0.218)	(0.346)	(0.380)	(0.472)
Difference	-0.252	-0.975**	-0.935**	0.040
	(0.261)	(0.440)	(0.436)	(0.569)
Plant FE	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes
Observations	35,717	35,717	35,717	35,717
KP F-stat	45.51	45.51	45.51	45.51

Notes: *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance. Standard errors in parentheses are clustered by plant. The dependent variable is the within (or intensive margin) Theil index in column (1), the logged number of products manufactured (scope) in column (2), the log of the partial sum process of positive changes in scope in column (3), and the log of the partial sum process of negative changes in scope in column (4). All dependent variables are based on value of sales. All regressions include a dummy for low productivity (LPROD) among the regressors.

To measure the effect of competition on plants' product mix, we estimate specifications similar to (7) with our measures of the within-plant composition of production as the dependent variable. Table 5 reports the results. Consistent with the multi-product firm literature, the within Theil index, T^W, increases with foreign competition. While there is a substantial difference in the estimated magnitude of the effect for high- and low-productivity plants, the difference is not statistically significant.

The estimates regarding the extensive margin measures paint a different picture. In contrast to the predictions of the multi-product firm literature, we find that the product scope of all plants increases with increased foreign competition relative to unaffected plants. We also find that the increase in scope is significantly smaller for low-productivity plants. This differential change points to product scope as a potential mediating factor of the diverging effect of competition on productivity.

Considering positive and negative changes in product scope separately, we see that the difference in the overall change in product scope across plants is driven by a differential response in product adding. While all plants add fewer products when faced with increased foreign competition, the effect is larger in magnitude for low-productivity plants.

Table 6: China effect on product adding by type at the plant level

Dependent variable	$\ln(N_{it})^{+}$ High machinery/capital ratio (1)	$\ln(N_{it})^{+}$ Low skill intensity (2)	$\ln(N_{it})^{+}$ Low capital intensity (3)
Chinese Mkt. Pen.	-0.781***	-0.887***	-0.714**
× High Productivity	(0.236)	(0.322)	(0.336)
Chinese Mkt. Pen.	-1.461***	-1.765***	-1.608***
× Low Productivity	(0.312)	(0.327)	(0.319)
Difference	-0.680**	-0.878**	-0.894**
	(0.292)	(0.355)	(0.371)
Plant FE	yes	yes	yes
Industry-Year FE	yes	yes	yes
Observations	35,717	35,717	35,717
KP F-stat	45.51	45.51	45.51

Notes: *** denotes 1% significance and ** denotes 5% significance. Standard errors in parentheses are clustered by plant. The dependent variable is the log of the partial sum process of positive changes in scope for products with machinery/capital ratio above the median in column (1), for products with skill intensity below the median in column (2), and for products with capital intensity below the median in column (3). All regressions include a dummy for low productivity (LPROD) among the regressors.

The overall positive effect of competition on product scope is driven by the response of product dropping. We find that all plants drop significantly fewer products when competition increases contrary to what theories of within-firm selection will predict.

To place the magnitude of these results into perspective, given the increase in Chinese market share of 9 percentage points over our sample period, the point estimates imply that Chinese competition made low-productivity plants about 8 percentage points less likely to add a product, which implies a similar lower increase in product scope. All other margins of within-plant reallocation − skewness of existing products and number of products dropped − are not differentially responsive to the rise in competition across low- and high-productivity plants.

While all plants see their sales become more concentrated in their top products in response to increased foreign competition, high-productivity plants additionally experience significant churning in the set of products that they produce, becoming more likely to add new products, and overall actually expand the set of products that they produce. By contrast, the low-productivity plants appear not to respond to Chinese competition along the extensive margin.

The divergence in extensive margin response across plants is suggestive that this may be an intermediate mechanism by which foreign competition affects productivity. To further examine this hypothesis, we investigate whether there are systematic differences in the type of products added by low- and high-productivity firms. We divide the products according to their relative input usage. Within an industry, products are categorised as low skill or low capital intensity if they are on average produced by plants with below median values for the share of white-collar workers or the capital-labour ratio. Similarly, products are defined to be high in machinery usage if they are produced by plants with an above median share of machinery and equipment in total capital.

Table 6 presents the results. We find that compared to high-productivity firms, low-productivity firms are significantly less likely to add low skill or capital intensity products, or products that are more intensive in machinery usage, with a rise in product market competition. Low skill and capital intensity products are presumably comparative advantage products for both low-productivity plants as well as Chinese competitors.[30] Rise in competition from China makes initially low-productivity plants less likely to experiment in new products closer their core competitiveness and also these firms are unable to invest into new products with significant machinery usage. Both dimensions of product adding potentially contribute towards the productivity loss observed among such firms.

Our empirical result on within-plant reallocation is somewhat in contrast to the predictions of the multi-product firm literature. While plants' sales do become more skewed toward their top products in response to increased competition, either types of plants are not found more likely to drop products. This lack of extensive margin response could be due to non-trivial fixed costs associated with shutting down product lines, viz. a type of exit cost which are ignored in Melitz-type models. Instead, it appears to be high-productivity plants' flexibility for expanding their product scope in the face of competition that alleviates the *negative* effect of competition on productivity compared to the low-productivity plants who do not respond as much in terms of product adding.[31]

[30] See Boehm et al. (2019) for a theory of comparative advantage of multi-product firms.

[31] This lack of within-plant reallocation or product-level dynamism is also observed unconditionally

Table 7: Product switching

Plant activity	All plants	Productivity Q1	Q2	Q3	Q4
None	86.4	85.2	88.3	86.9	84.9
Drop product(s) only	5.2	5.8	4.7	5.0	5.3
Add product(s) only	4.1	3.8	3.7	4.3	4.5
Both add and drop	4.3	5.1	3.1	3.8	5.3

Notes: The table reports average percent of plants engaging in each type of product-changing activity from year to year. The four plant activities are mutually exclusive. Q1, Q2, Q3 and Q4 refer to the four quartiles of plants' productivity.

5.3 Discussion

Thus, lack of within-plant reallocation is a plausible candidate for the kind of loss in productivity observed among initially low productivity plants in the face of rising Chinese competition in Mexico. However, lack of within-plant reallocation is by no means sufficient to explain the kind of loss in efficiency we observe because loss in productivity or rise in marginal cost of production happens not only at the plant-level, but also at the plant-product level.

TFPQ is our preferred measure of productivity. However, the procedure we use to estimate TFP also yields estimates of marginal cost. While marginal cost depends on additional factors, such as input prices and economies of scale, our marginal cost estimates have the relative advantage of varying by product and market within a plant. This feature allows us to control for any product- and market-specific factors that might be correlated with both plant-level productivity and competition from China. We find robust evidence that products below median sales (within a plant) experience an increase in marginal cost, consistent with declining productivity, with increase in competition from China.[32]

We explore a number of alternative channels which can potentially explain the loss in productivity such as export participation, investment and imported inputs. However, none of them prove to be of any additional empirical relevance in this context. We relegate this discussion in the appendix.

It is also plausible that our results depend on the distribution of the shock to com-

among low-productivity plants as Table 7 reveal. Plants at higher quartiles of productivity are substantially more likely to drop and add products on average.

[32]The results are presented in the Appendix in Table 11.

petition across plants' products. For example, if the better-performing products of low-productivity plants are more likely to face increased competition, then this may explain why such plants appear to be more affected. The results, presented in Table 13 in the Appendix, show that the increased competition from China was similarly distributed across different products of high- and low-productivity plants. Therefore, the distribution of competition shocks is unlikely to be a significant driver of any of our results.[33]

Finally, it is worth pointing out that although competition from China resulted in a relative fall in productivity for initially lower performing firms, this does not mean that the growth of China was welfare reducing for Mexico. In addition to having access to new and cheaper Chinese products, Mexican consumers and producers may benefit – and industry-level efficiency may increase – from the pro-competitive effects of Chinese competition through lower markups of Mexican producers, at least for those at the bottom of the productivity distribution. Evidence for this pro-competitive effect is presented in the appendix. Thus, welfare implications of increased competition from China is multi-faceted.

6 Conclusion

The rise of China has had a profound effect on economies worldwide. This paper has studied the effect of increasing competition from Chinese producers on productivity in a middle-income country, Mexico. This is particularly relevant today considering the productivity slowdown that economies around the world have been observing and the fact that middle-income countries are more likely than developed countries to be affected by China.

We find a significant heterogeneous impact of the rise of China on productivity of Mexican plants. Indeed, we find that exposure to foreign competition leads to reduced productivity of ex-ante low-productivity plants in Mexico. This heterogeneous response

[33]Note that this regression is not meant to estimate a causal effect, only to demonstrate how the relative increase in competition from Chinese exporters is correlated with the plants' ex-ante sales distribution.

resembles the outcomes in the model by Aghion et al. (2009), in which there are offsetting effects of increased competition on innovation incentives: a Schumpeterian appropriability effect which reduces the returns to innovation and an “escape-competition effect” which increases the returns to innovation by more for firms close to the technological frontier. The effect of competition on productivity that we find is in contrast to the effects found in developed countries, such as Bloom et al. (2016), and consistent with low-productivity Mexican plants lagging behind Chinese entrants. We find that a potential explanation for such productivity divergence is the lack of experimenting with new products in line with comparative advantage among low-productivity plants but not for high-productivity plants.

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Appendix

A Robustness

Table 8: China effect on productivity at the plant level - Quantile regressions

	FE	IV1	IV2
	(1)	(2)	(3)
25th Percentile			
Chinese Market	-1.732**	-5.170***	-6.010***
Penetration	(0.708)	(1.290)	(1.046)
50th Percentile			
Chinese Market	-0.692	-4.139***	-1.654**
Penetration	(0.423)	(1.083)	(0.697)
75th Percentile			
Chinese Market	-0.500	-0.854	-0.542
Penetration	(0.611)	(0.902)	(0.764)
Observations	36,149	36,149	36,149

Notes: *** denotes 1% significance, and ** denotes 5% significance. Standard errors in parentheses are clustered by plant. The dependent variable is the log of total factor productivity. The quantile regressions control for plant and year fixed effects.

Table 9: China effect on productivity at the plant level, lagged dependent variable

	(1)	(2)	(3)
Chinese Mkt. Pen.	0.812*	1.378	3.237***
× High Productivity	(0.420)	(0.979)	(1.226)
Chinese Mkt. Pen.	-0.605	-4.863***	-5.742***
× Low Productivity	(0.399)	(1.167)	(1.329)
Difference	-1.416**	-6.241***	-8.979***
	(0.696)	(1.627)	(2.086)
Productivity (log), lag	0.468***	0.464***	0.464***
	(0.102)	(0.103)	(0.103)
Plant FE	yes	yes	yes
Industry-Year FE	yes	yes	yes
Observations	36,149	36,149	36,149

Notes: *** denotes 1% significance, and ** denotes 5% significance. Standard errors in parentheses are clustered by plant. The dependent variable is the log of total factor productivity. All regressions include a dummy for low productivity (PROD) among the regressors. All regressions are estimated with system GMM and instrument lagged productivity with twice-lagged productivity.

Table 10: China effect on lagged productivity at the plant level, test for pre-trend

	FE	IV1	IV2	FE	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Mkt. Pen.	0.018	-0.378	-0.252	0.252	0.157	0.668
× High Productivity, 5-year lag (β_1^p)	(0.196)	(0.450)	(0.405)	(0.258)	(0.720)	(0.661)
Chinese Mkt. Pen.	-0.223	-1.562**	-1.337**	0.162	-0.520	0.255
× Low Productivity, 5-year lag ($\beta_1^p + \beta_2^p$)	(0.285)	(0.759)	(0.636)	(0.279)	(1.231)	(0.995)
Difference (β_2^p)	-0.241	-1.184	-1.086	-0.091	-0.677	-0.413
	(0.366)	(0.923)	(0.804)	(0.326)	(1.274)	(1.087)
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	No	No	No
Industry-Year FE	No	No	No	Yes	Yes	Yes
Observations	22,012	22,012	22,012	21,895	21,895	21,895
KP F-stat		20.83	47.05		28.03	39.22

Notes: *** denotes 1% significance, and ** denotes 5% significance. Standard errors in parentheses are clustered by plant. The dependent variable is the five lag of the log of total factor productivity. All regressions include a dummy for 5-year lag of low productivity (PROD) among the regressors.

B Discussion and Alternative Channels

Effect of Competition on Marginal Costs and Markups

We estimate the following specification for marginal costs

$$\begin{aligned}\ln mc_{ijkt} =&\beta_1^{mc}\text{MP}^{\text{CH}}_{jk,t-1} + \beta_2^{mc}\text{MP}^{\text{CH}}_{jk,t-1} \times \text{PROD}_{it} + \beta_3^{mc}\text{MP}^{\text{CH}}_{jk,t-1} \times \text{Bottom}_{ijkt}+\\ &\beta_4^{mc}\text{MP}^{\text{CH}}_{jk,t-1} \times \text{PROD}_{it} \times \text{Bottom}_{ijkt} + \rho_1^{mc}\text{PROD}_{it} + \rho_2^{mc}\text{Bottom}_{ijkt}+\\ &\rho_3^{mc}\text{PROD}_{it} \times \text{Bottom}_{ijkt} + \gamma_{ijk}^{mc} + \delta_t^{mc} + \epsilon_{ijkt}^{mc},\end{aligned} \tag{9}$$

and a similar one for markups

$$\begin{aligned}\ln \mu_{ijkt} =&\beta_1^{\mu}\text{MP}^{\text{CH}}_{jk,t-1} + \beta_2^{\mu}\text{MP}^{\text{CH}}_{jk,t-1} \times \text{PROD}_{it} + \beta_3^{\mu}\text{MP}^{\text{CH}}_{jk,t-1} \times \text{Bottom}_{ijkt}+\\ &\beta_4^{\mu}\text{MP}^{\text{CH}}_{jk,t-1} \times \text{PROD}_{it} \times \text{Bottom}_{ijkt} + \rho_1^{\mu}\text{PROD}_{it} + \rho_2^{\mu}\text{Bottom}_{ijkt}+\\ &\rho_3^{\mu}\text{PROD}_{it} \times \text{Bottom}_{ijkt} + \gamma_{ijk}^{\mu} + \delta_t^{\mu} + \epsilon_{ijkt}^{\mu},\end{aligned} \tag{10}$$

where we include a full set of interactions between MP^{CH} and dummies for low productivity (PROD) and for whether a product is below the median ranking of sales within each plant-market-year triplet (Bottom) as well as plant-product-market fixed effects.

The results are reported in Table 11, where the first three columns refer to the effects on marginal costs and the last three columns to the effects on markups. In a similar vein to our results for TFP, we find that increased foreign competition causes a rise (significant in most cases with IV) in marginal costs for all plants and products, except for above-median products in high-productivity plants (coefficient β_1^{mc}). Indeed, the coefficient on Chinese market penetration for above-median products in high-productivity plants is always smaller and statistically different (at least at the 5% level) from the coefficients for the other three categories (high-productivity/below-median, low-productivity/above-median, and low-productivity/below-median).

Equivalently, we find that increased foreign competition causes a decrease in markups for all plants and products, except for above-median products in high-productivity plants

Table 11: China effect on marginal costs and markups

	Marginal costs			Markups		
	FE	IV1	IV2	FE	IV1	IV2
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese Mkt. Pen.	0.212	0.395	-1.026	-0.214	-0.548	0.935
× High Productivity	(0.169)	(0.785)	(0.660)	(0.154)	(0.718)	(0.639)
× Top Product (β_1)						
Chinese Mkt. Pen.	0.281	2.020***	1.072*	-0.317	-2.101***	-1.012*
× Low Productivity	(0.191)	(0.752)	(0.596)	(0.207)	(0.757)	(0.579)
× Top Product ($\beta_1 + \beta_2$)						
Chinese Mkt. Pen.	0.234	2.461***	1.176**	-0.261*	-2.541***	-1.174**
× High Productivity	(0.153)	(0.788)	(0.578)	(0.137)	(0.698)	(0.535)
× Bottom Product ($\beta_1 + \beta_3$)						
Chinese Mkt. Pen.	0.0790	1.755***	0.694	-0.0694	-1.866***	-0.612
× Low Productivity	(0.140)	(0.619)	(0.515)	(0.142)	(0.640)	(0.520)
× Bottom Product ($\beta_1 + \beta_2 + \beta_3 + \beta_4$)						
Difference (β_2)	0.069	1.625**	2.098***	-0.103	-1.553**	-1.947***
	(0.245)	(0.786)	(0.722)	(0.246)	(0.764)	(0.683)
Difference (β_3)	0.022	2.065***	2.202***	-0.047	-1.994***	-2.109***
	(0.167)	(0.470)	(0.443)	(0.151)	(0.457)	(0.427)
Difference ($\beta_2 + \beta_3 + \beta_4$)	-0.133	1.360**	1.720***	0.144	-1.318**	-1.547**
	(0.215)	(0.667)	(0.615)	(0.206)	(0.648)	(0.621)
Plant-Product-Market FE	yes	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes	yes
Observations	100,521	100,521	100,469	100,521	100,521	100,469
KP F-stat		17.03	18.40		17.03	18.40

Notes: *** denotes 1% significance, ** denotes 5% significance, and * denotes 10% significance. Standard errors in parentheses are clustered by 8-digit INEGI product category. The dependent variable is the log of marginal costs at the plant-product-market level in the first two columns and the log of markups at the plant-product-market level in the last two columns. All regressions include a dummy for low productivity (PROD), a dummy for whether a product is below the median ranking of sales within each plant-market-year triplet (Bottom) and their interaction among the regressors.

(coefficient β_1^μ). The coefficient on Chinese market penetration for above-median products in high-productivity plants is always larger (less negative) and statistically different (at least at the 5% level) from the coefficients for the other three categories (high-productivity/below-median, low-productivity/above-median, and low-productivity/below-median). Incidentally, these results also imply that there is no effect on prices for any category.

Alternative Channels

Table 12: China effect on other channels at the plant level

Dependent variable	Export	Import Materials	Import Machinery	Investment Machinery	Investment Building
	(1)	(2)	(3)	(4)	(5)
Chinese Mkt. Pen.	0.042	-0.033	0.693	0.086	0.948
× High Productivity	(0.098)	(0.159)	(0.601)	(2.058)	(1.493)
Chinese Mkt. Pen.	-0.055	0.317⋆	1.061	4.256	-0.100
× High Productivity	(0.111)	(0.167)	(1.079)	(2.934)	(2.352)
Difference	-0.097	0.350⋆⋆	0.368	4.171	-1.048
	(0.123)	(0.178)	(0.664)	(3.186)	(2.525)
Plant FE	yes	yes	yes	yes	yes
Industry-Year FE	yes	yes	yes	yes	yes
Observations	35,717	35,717	35,717	34,344	35,014
KP F-stat	45.51	45.51	45.51	43.52	45.10

Notes: ⋆⋆ denotes 5% significance, and ⋆ denotes 1% significance. Standard errors in parentheses are clustered by plant. The dependent variable is export intensity in column (1), share of imported materials in column (2), share of imported machinery and equipment in column (3), logged investment in machinery and equipment plus one in column (4), and logged investment in buildings and structures plus one in column (5).

Distribution of the China Shock

To test whether this phenomenon may drive our results, we estimate an equation of the form

$$\mathrm{MP}^{\mathrm{CH}}_{jkt} = \beta^C_0 + \beta^C_1 \mathrm{PROD}_{it} + \beta^C_2 \mathrm{Bottom}_{ijkt} + \beta^C_3 \mathrm{PROD}_{it} \times \mathrm{Bottom}_{ijt} + \epsilon_{it},$$

where PROD_{it} is an indicator for a plant with productivity below the median, and Bottom_{ijt} is an indicator for a product with sales below the median within the plant. The coefficient on the interaction these two variables, β^C_3 measures the extent to which competition from Chinese exports increases by more on average for the bottom products of low-productivity plants.

Table 13: China effect by plant and product type

	FE (1)	FE (2)
Low Productivity	0.0000 (0.0003)	0.0001 (0.0004)
Bottom Product	0.0000 (0.0003)	0.0001 (0.0004)
Low Productivity × Bottom Product		-0.0002 (0.0005)
Product-Market FE	yes	yes
Industry-Year FE	yes	yes
Observations	118,528	118,528
R^2	0.878	0.878

Notes: Standard errors in parentheses are clustered by 8-digit INEGI product category. The dependent variable is the share of Chinese imports by product-market-year.

Plant Exit

Table 14: China effect on plant exit

	FE	IV1	IV2
	(1)	(2)	(3)
Chinese Mkt. Pen.	0.031	0.012	0.017
× High Productivity	(0.052)	(0.161)	(0.133)
Chinese Mkt. Pen.	0.002	-0.078	-0.011
× Low Productivity	(0.054)	(0.198)	(0.146)
Difference	-0.030	-0.090	-0.028
	(0.065)	(0.218)	(0.156)
Plant FE	yes	yes	yes
Industry-Year FE	yes	yes	yes
Observations	35,717	35,717	35,717
KP F-stat		45.51	77.05

Notes: Standard errors in parentheses are clustered by plant. The dependent variable is a dummy equal to one if a plant exits the market.