Asia Competitiveness Institute

ACI Research Paper #14-2022

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Please cite this article as:

Banh, Thi Hang and Mauro Caselli, "Foreign Competition, Skill Premium, and Product Quality: Impact of Chinese Competition on Mexican Plants", Research Paper #14-2022, *Asia Competitiveness Institute Research Paper Series (August 2022).*

Foreign Competition, Skill Premium, and Product Quality: Impact of Chinese Competition on Mexican Plants*

Thi Hang Banh[†] and Mauro Caselli[‡]

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Abstract

This paper analyses the effect of rising competition from Chinese exports on the skill premium of Mexican plants. Using detailed product-plant-level production data from Mexico and bilateral product-level trade data for 1994-2007, we provide evidence that Mexican plants reduce their skill premium in response to increasing competition from Chinese exports, and the effect is more pronounced among non-exporting plants. Thus, we develop a model linking competition and wage inequality between skilled and unskilled workers by introducing these two types of labour to a model with heterogeneous firms and quality differentiation. Our model predicts that tougher competition leads plants to downgrade quality, which induces a decline in the wage difference between skilled and unskilled workers. We investigate this hypothesis empirically by analysing the effect of Chinese competition on the product quality of Mexican plants. Consistent with the fall in the skill premium, we document a downgrading impact of China's rise on Mexican plants' product quality and this quality downgrading is less intense for products sold in the foreign market. These findings provide empirical support for the predictions of our model.

Keywords: product quality, Chinese competition, skill premium, Mexico, heterogeneous firms.
JEL Codes: D21, D22, F12, F14.

*Thi Hang Banh would like to thank her supervisors, Arpita Chatterjee and Arghya Ghosh, for many helpful comments and discussions, as well as for their guidance during her PhD program. We thank Reshad Ahsan, Anirudh Yadav, the anonymous reviewer of the John McMillan award at the UNSW School of Economics, and participants at the UNSW School of Economics PhD seminar series for their supportive comments and suggestions. All errors are our own.

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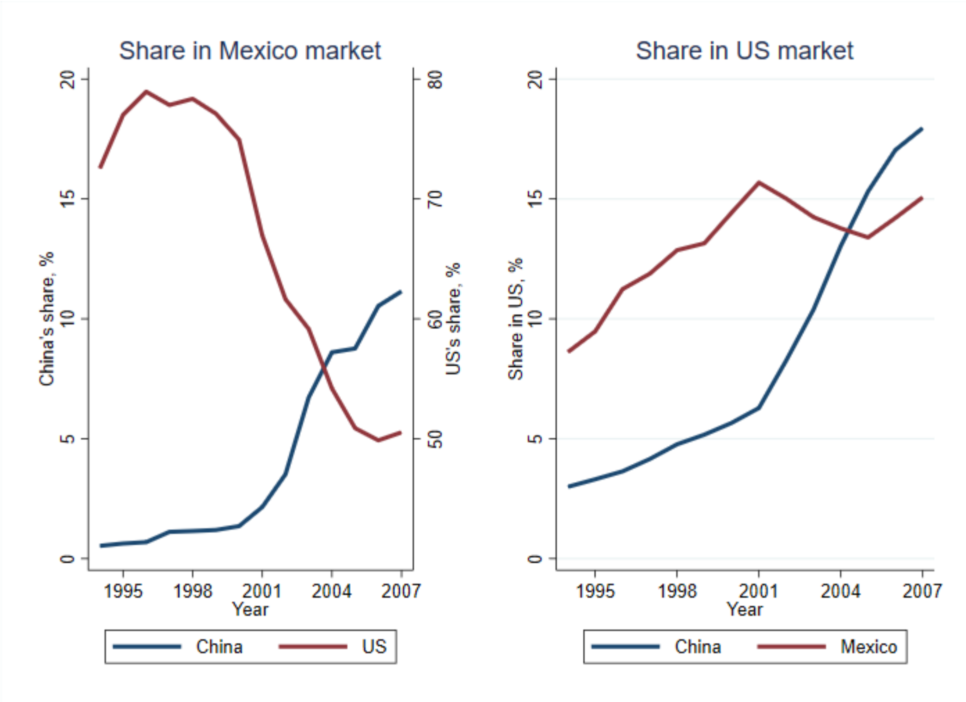
1 Introduction

Over the past thirty years, the effect of international trade on wage inequality has been the subject of intense debate. Recently, with the rapid rise of China, the largest labour-intensive country in the world, a growing body of research has focused on the impact of Chinese import competition on the labour market in developed countries (e.g., Autor, Dorn, & Hanson, 2013). While all countries are affected by the rapid integration of China in world markets, one might expect the effects to be most immediate in those middle-income countries whose established positions in manufacturing markets have come under threat. Consequently, workers in these middle-income countries might at greater risk due to the rise of China. However, there has been a lack of attention on the impact of Chinese competition on the labour market in developing countries, especially middle-income countries.

In this paper, we analyse how the increasing competitive pressure from China affects wage inequality in Mexican plants. We combine detailed plant-level panel data for Mexican plants from 1994 to 2007 with data on product-level bilateral trade flows from the United Nations (UN) COMTRADE database. In this period, the share of China's manufacturing goods in the US total manufacturing imports increased from about 7.2% to more than 19.3%, while Mexico's share rose only from about 7% to around 10%, despite the signing of the North American Free Trade Agreement (NAFTA) in 1994. The share of China in Mexican manufacturing imports grew from about 0.7% to around 11% (see figure 1), presenting a major competitive threat to domestic Mexican producers. At the same time, there was a substantial increase in the white-collar to blue-collar wage ratio in Mexico after 1984, reaching a peak in 1996-1998 (Verhoogen, 2008).

We relate changes in exposure to Chinese imports to changes in the skill premium, i.e. white-collar to blue-collar wage ratio, in Mexican plants. One striking feature of the Mexican plant-level data is that workers are categorised into occupation types, i.e., white-collar and blue-collar workers, which allows us to measure the skill premium at the plant level. Moreover, values and quantities at the product-plant level are separated between domestic and export sales, allowing us to capture the effect of Chinese competition in both domestic (i.e., Mexico) and foreign (i.e., US) markets. Chinese competition is measured by the weighted sum of the share of China's exports to the US and the share of China's exports to Mexico. We use a shift-share instrument to address the potential endogeneity of the measure of Chinese competition (Bartik, 1991). In particular, we instrument the share of China in the US market with the share of China's exports in other high-income countries and the share of China in Mexico with the share of China's exports in comparable South American countries (Autor et al., 2013). We find evidence that Chinese competition leads to a fall in the skill premium of Mexican firms, and the effect on non-exporting firms is more prominent than on exporters.

Figure 1: Shares of China in the Mexican and the US markets



Source: UN COMTRADE database. The figure presents the share of total imports from each country in Mexico's/US's total imports.

We link competition and changes in the skill premium via adjustments in quality at the plant level by proposing a model of heterogeneous firms with endogenous quality choice, skilled workers heterogeneous across firms, and endogenous wages of skilled workers. The model is based on Antoniades (2015) and Melitz and Ottaviano (2008) with linear demand systems and endogenous quality choice but extended to include two factors of production, which are unskilled and skilled workers. On the demand side, goods are differentiated in quality and consumers have a preference for both quantity and quality of varieties (Foster, Haltiwanger, & Syverson, 2008). On the supply side, plants are heterogeneous in productivity, and there is a fixed cost of quality upgrading that is invariant to output. We introduce two factors of production to the model by assuming that firms use unskilled labour to produce physical output and skilled labour to produce quality. The production of higher-quality goods requires higher-quality workers, and higher-quality workers are paid higher wages in equilibrium. Our model predicts that tougher competition leads firms to downgrade their product quality, which induces a decline in the skill premium at the firm level.

Subsequently, we investigate the empirical implication of our model by examining the effect of Chinese competition on product quality. Product quality at the product-plant-market level is estimated following the methodology in Khandelwal, Schott, and Wei (2013). We find that Mexican plants downgrade the quality of their products in response to rising competition from China. The effect is less strong for products sold in the foreign market. The empirical findings are consistent with the predictions of the model.

To the best of our knowledge, our finding on the negative effect of competition on product quality and the skill premium is novel. There has been no theoretical model and empirical evidence showing this result. In particular, Amiti and Khandelwal (2013) find that greater competition in the home market leads to an increase in export quality. In our model, an increase in the number of firms in the market reduces the cost cutoff between firms that operate in the market and those that exit. This decline in the cost cutoff decreases the marginal benefit of quality upgrading but does not affect the marginal cost of quality upgrading. Therefore, firms downgrade product quality rather than invest in quality upgrading.

In addition to the papers cited above, our paper is related to a number of different strands of the literature. First, we contribute to the rapidly growing literature on the impact of the China trade shock on other countries. The literature focuses on the effect of Chinese competition on firm outcomes such as total factor productivity (Bloom, Draca, & Van Reenen, 2016) and firms' market power (Caselli, Nesta, & Schiavo, 2021; Caselli & Schiavo, 2020); labour market outcomes such as job loss, unemployment, or labour force participation in high-income markets such as the US (Acemoglu, Autor, Dorn, Hanson, & Price, 2016; Autor, Dorn, Hanson, & Song, 2014) or European countries (Utar, 2018); or product variety (Chakraborty & Henry, 2019). Instead, we investigate the effect of the rise of China on wage inequality in a middle-income country.

There have also been papers on the effect of Chinese competition on Mexican plants and the labour market. Utar and Ruiz (2013) study the impact of Chinese competition in Mexico and find a positive impact of Chinese competition on wage inequality, but they concentrate on Mexican export processing plants (maquiladoras) and competition in the US market. By contrast, our study excludes maquiladora plants, and we provide evidence of a negative effect of Chinese competition on the skill premium. Maquiladora plants are distinctly different from plants in our sample in the sense that maquiladoras import inputs mostly from the US, process them, and then ship them back. Maquiladoras are also largely duty-free and tariff-free. Also, since our data include plants selling in both domestic and foreign markets, we capture the competition from China in both the US and Mexico. Mendez (2015) also analyses the impact of Chinese competition on the labour market in Mexico. However, the paper uses data at the five-digit SITC (the Standard International Trade Classification) level, and thus cannot take into account the heterogeneity between products and plants at a more disaggregated level. Caselli, Chatterjee, and French (2021) focus on the effect of Chinese competition on productivity and within-plant allocation of Mexican plants using the same Mexican manufacturing plant-level dataset.

Second, our paper relates to the literature examining the determinants of changes in the relative wage of skilled workers, especially in Mexico. Some papers show that trade liberalisation contributed to a fall in wage inequality (Amiti & Cameron, 2012; Chiquiar, 2008; Robertson, 2004). On the other hand, Verhoogen (2008) proposes that quality upgrading induced by the exchange-rate shock increased within-industry wage inequality. Caselli (2014) provides evidence for positive effects of skill-biased technical change on the skill premium in Mexico. Hummels, Jorgensen, Munch, and Xiang (2014) document that offshoring increased wage inequality. Similarly, Waddle (2021) argues that trade liberalization led to a rise in the skill premium of Mexican plants and industries that traded more with the United States through technology transfers from US firms. We investigate how foreign competition drove changes in the skill premium in Mexico and propose a channel, i.e., changes in quality, through which foreign competition could affect the skill premium.

Given the quality channel, our paper is particularly related to Verhoogen (2008). However, his model defines a production function for product quality, leaving aside product quantity, and it focuses on the impact of exchange rate shocks rather than the effect of foreign competition. In our model, we explicitly incorporate product quality into a production function with endogenous choices of both quantity and quality. Our utility function and production function allow us to investigate the impact of competition on product quality and link it to changes in the skill premium.

Third, our research contributes to the literature on product quality and innovation (Aghion, Bergeaud, Lequien, & Melitz, 2018; Amiti & Khandelwal, 2013; Fan, Li, & Yeaple, 2015). Within this literature, our paper is most closely related to Amiti and Khandelwal (2013). While also investigating the impact of competition on product quality, our paper differs from Amiti and Khandelwal (2013) in several ways. First, they focus on the effect of import competition, which is measured by a decrease in tariffs, on quality upgrading, whereas our focus is on the effect of competition on the skill premium. Product quality adjustment is a mechanism linking competition to the skill premium in our paper. Second, we use a different measure of competition, which is the share of imports from China in a given market, and consider competition in both home and foreign markets. Third, by using firm-level data and measuring China's share at the plant level, we take into account heterogeneity across plants in the magnitude of the shock.

The remainder of the paper is organised as follows. In Section 2, we describe the data used in this paper and we provide evidence of the effect of competition on the skill premium that motivates the rest of the analysis. Section 3 presents a model that provides a mechanism linking competition and the skill premium via product quality. Section 4 empirically tests the model's predictions by investigating the impact of the rise of China on product quality. Robustness checks for our empirical results are presented in Section 5. Section 6 concludes.

2 Data and the effect of competition on the skill premium

In this section, we describe the data used in this paper and briefly discuss how the skill premium has changed in Mexico over the period analysed. We also describe our measure of Chinese competition and our strategy to deal with endogeneity concerns when studying the effect of competition on the skill premium. Then, we show the effect of Chinese competition on the skill premium of Mexican plants and how this effect varies according to productivity and export status.

2.1 Data and summary statistics

We use manufacturing plant-level data from two surveys collected by the Mexican Instituto Nacional de Estadística y Geografía (National Institute of Statistics and Geography, henceforth INEGI) and covering the period 1994-2007. The two surveys are the Encuesta Industrial Anual (Annual Industrial Survey, henceforth EIA), the main survey covering the manufacturing sector, and the Encuesta Industrial Mensual (Monthly Industrial Survey, henceforth EIM), a monthly survey monitoring short-term trends. The EIM has traditionally been run in parallel with the EIA and covers the same plants based on the 1993 Economic Census. However, the EIA was updated in 2003 to include new plants. Since our analysis uses information from both EIA and EIM, we include only plants present in both the EIM and EIA in the estimation. We aggregate monthly values in the EIM into annual data and match them with information from the EIA survey using a unique plant identifier provided by INEGI. Next, we describe the main variables present in these two datasets. Further information about the surveys is provided by Iacovone (2008) and Caselli, Chatterjee, and Woodland (2017).

The EIA covers 6,867 plants in 1994, but this number decreases over time due to attrition. Because of the sampling method, the EIA is skewed towards larger plants and represents about 85 percent of the total Mexican industrial output. It covers 205 of the 309 six-digit classes of the 1994 Clasificación Mexicana de Actividades y Productos (Mexican System of Classification for Activities and Products, henceforth CMAP). However, "export maquiladoras", i.e., firms that import most intermediate inputs and export most of their output on a duty-free and tariff-free basis, are excluded from the EIA. The EIA contains information on output indicators, inputs, and investment. We use this survey's data on inputs (e.g., material expenditures, total employment, and capital), investment, import and export status, and geographical region.

The EIM captures two groups of variables: labour-force-related and output-related variables. Labour-force-related variables include the number of workers, their wage bills, and the number of hours worked by occupation type. Workers are broken down into white collars (or non-production), such as managers, administrators, professionals, and salespeople, and blue collars (or production), whose main activities include machine operation, production supervision, repair, maintenance, and cleaning.

Output-related variables contain information on values and quantities of production and sales, both for the domestic and export markets, at the product-plant level. The separation of products between domestic and export sales is a novel feature of EIM, allowing us to capture the effect of competition from Chinese exports in both domestic and foreign markets. The data does not include the destination of exports. However, as more than 80% of exports from Mexican plants go to the US during the period examined, we assume that all exported products were destined for that country. An implicit average product-plant-level unit price can also be obtained using the information on values and quantities at the product-plant level. The information on unit price allows us to estimate quality at the product-plant level. Products are disaggregated at the eight-digit level according to a list provided by INEGI for each six-digit class of activities.

The distinction between non-production and production workers is another unique feature of EIM that allows us to measure the skill premium at the plant level. We use non-production workers to identify skilled labour and production workers to identify unskilled labour. Throughout the paper, the skill premium is measured as the ratio of the average wage for white-collar workers to the average wage for blue-collar workers. While there are problems with this measure of the skill premium (Leamer, 1994), it is common in the literature because it is often the only one available in firm-level data (Feenstra & Hanson, 1997; Verhoogen, 2008).

Table 1 shows the summary statistics of the main plant-level variables. Plants are split into exporters and non-exporters on the basis of their first year available in the sample. The table shows that the majority of plants in the sample are non-exporters. On average, exporting plants employ a higher number of employees, including both skilled and unskilled workers, and pay higher wages than non-exporting plants.

In Table 1, the skill intensity is largely similar between exporting plants and non-exporting ones.[1] On the other hand, the distribution of the skill premium of exporters is more skewed toward the upper tail than the skill premium of non-exporters (see Figure A2 in Appendix A). This difference in the distributions is consistent with the theoretical predictions and empirical findings of the literature on exporters and wage inequality, i.e., there is a larger export wage premium for skilled workers than for low-skilled workers (Helpman, Itskhohi, & Redding, 2010; Klein, Moser, & Urban, 2013).

[1] Figure A1 in Appendix A also shows no considerable difference in the distributions of skill intensity between exporters and non-exporters.

Table 1: Summary statistics

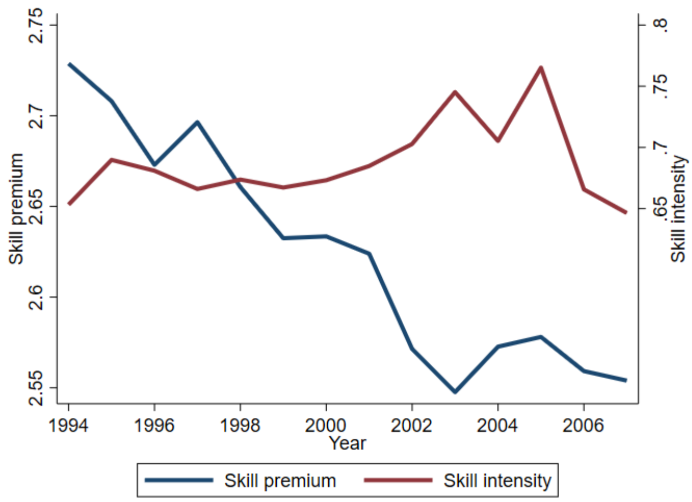
	All firms			Non-exporters			Exporters		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
Number of employees	2	286.59	14479	2	226.66	7993	3	465.47	14479
Number of skilled workers	1	90.54	6576	1	74.76	6576	1	137.63	4926
Number of unskilled workers	1	196.05	10878	1	151.9	5338	2	327.84	10878
Skill intensity	0	0.69	148	0.01	0.68	148	0	0.69	111.5
Wage of skilled workers (log)	1.2	4.32	7.16	1.2	4.22	7.16	1.56	4.62	6.98
Wage of unskilled workers (log)	0.25	3.48	6.52	0.25	3.42	6.52	0.89	3.64	6.19
Skill premium (log)	-0.48	0.84	2.17	-0.48	0.8	2.17	-0.48	0.98	2.17
Number of plants		4440			3405			1035	
Number of observations		44686			33472			11214	

Notes: Skill premium is the ratio of the wage of skilled workers to the wage of unskilled workers. Skill intensity is the ratio of the number of skilled workers to the number of unskilled workers. Plants are split into exporters and non-exporters on the basis of their first year available in the sample. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles.

Regarding the evolution of wage inequality in Mexico, the literature has shown that it increased significantly after 1985 when Mexico joined the General Agreement and Tariffs and Trade (GATT) (Caselli, 2014; Esquivel & Rodríguez-López, 2003; Feenstra & Hanson, 1997). However, when the North American Free Trade Agreement (NAFTA) came into effect in 1994, inequality started showing a diminishing trend (Bosch & Manacorda, 2010; Robertson, 2004).

This decrease in inequality can also be observed in our data. Figure 2 shows the evolution of average relative wages and employment of skilled and unskilled workers in our sample of Mexican plants between 1994 and 2007. The figure shows that the real average wage of non-production workers in Mexico's manufacturing industry was about 2.7 times larger than the real average wage of production workers in 1994, but this ratio decreased over the period considered, in particular from 1997 onward. On the other hand, the average employment ratio remained roughly constant during the period from 1994 to 2007.

Figure 2: Skill premium and skill intensity in Mexican manufacturing



Source: INEGI database. The skill premium is defined as the white-collar to blue-collar wage ratio and the skill intensity is defined as the white-collar to blue-collar employment ratio.

In addition to the plant-level data, this paper uses annual product-level trade data from the UN COMTRADE database (United Nations Statistics Division, 2011). The dataset provides information on bilateral trade, including trade values and unit values at the six-digit Harmonized System (HS6, 1992 version) product disaggregation. The dataset contains 5129 product categories with positive US imports over the period 1994-2007. Since there is no concordance available between HS6 classification and the eight-digit Mexican product classification, we use a manual match provided by Caselli, Chatterjee, and French (2021). More than 3,000 eight-digit products in the manufacturing plant-level data are matched to one or sometimes multiple HS codes using the product description provided by INEGI.

2.2 Skill premium and competition

In the previous sections, we have seen that during the period 1994-2007 the Mexican plants in our sample showed a decrease in the skill premium and, at the same time, faced stronger Chinese competition, both in the domestic and export markets. While this provides *prima facie* evidence of a negative relationship between the skill premium and Chinese competition, next we provide a formal analysis of such relationship.

First, we measure product market competition faced by Mexican plants from China as the share of imports from China in a given product and market. Because the vast majority of Mexican exports go to the US, we consider two markets, the Mexican market and the US import market. Given that the skill premium is measured at the plant level, we aggregate our measure of Chinese competition over products and markets, using revenue shares in the first year available as weights to mitigate any endogeneity concerns. Thus, our Chinese competition for plant i in year t is given by:

$$China\ share_{it} = \sum_d \sum_k \frac{X_{idk0}}{\sum_d \sum_k X_{idk0}} \frac{M^C_{dkt}}{M_{dkt}}, \tag{2.2.1}$$

where X_{idk0} is the volume of sales of product k produced by plant i and sold in market d in the first year available, and $China\ share_{dkt} = \frac{M^C_{dkt}}{M_{dkt}}$ is the share of imports from China of product k in market d (M^C_{dkt}) in total imports of product k in market d (M_{dkt}) in year t.

We use the following empirical specification to relate the skill premium to Chinese competition:

$$Log(Skill\ premium)_{it} = \beta China\ share_{i,t-1} + \alpha_i + \alpha_{rt} + \alpha_{st} + \varepsilon_{it}. \tag{2.2.2}$$

The dependent variable $Log(Skill\ premium)_{it}$ refers to the log of the skill premium of plant i at time t. Our specification includes plant fixed effects (α_i), region-year fixed effects (α_{rt}), and sector-year fixed effects (α_{st}). The plant fixed effects capture plants' time-invariant characteristics. The region-year fixed effects control for region-level shocks, such as labour supply shocks or region characteristics, e.g., border regions are more linked to international markets than others. The sector-year fixed effects sweep out sectoral level shocks, such as demand shocks or worldwide technology shocks. ε_{it} is an idiosyncratic error term.

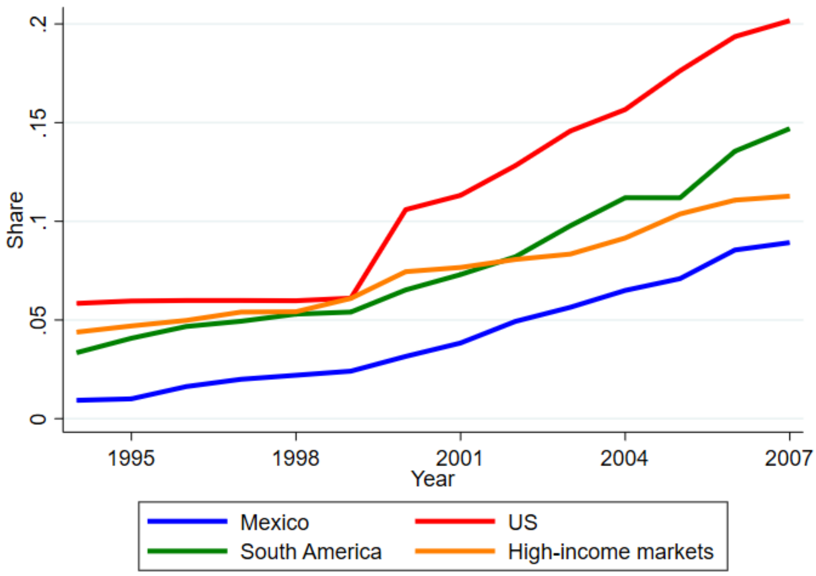
Despite the inclusion of a large set of fixed effects and the use of lagged values for our main explanatory variable, $China\ share_{i,t-1}$, the estimate of β in equation (2.2.2) may be biased due to endogeneity arising from omitted variables, such as demand shocks or other market conditions, which would be included in the error term and are potentially correlated with competition from China. For example, if high import demand from Mexico or the US causes new Chinese firms to enter the market, our estimates would likely be biased toward zero. Thus, we instrument for $China\ share_{i,t-1}$ using a shift-share instrumental variable (IV) (Bartik, 1991), following a strategy similar to Autor et al. (2013). Specifically, we construct a market-specific IV, which is equal to China's import share in a set of middle-income South American countries for the Mexican market and that in high-income developed countries for the US market. Thus, our IV can be written as follows:

$$China\ share\_IV_{it} = \sum_k \frac{X_{iMEXk0}}{\sum_d \sum_k X_{idk0}} \frac{M^C_{SAkt}}{M_{SAkt}} + \sum_k \frac{X_{iUSk0}}{\sum_d \sum_k X_{idk0}} \frac{M^C_{HIkt}}{M_{HIkt}}, \tag{2.2.3}$$

where $\frac{M^C_{SAkt}}{M_{SAkt}}$ is the share of imports from China of product k in middle-income South American markets (M^C_{SAkt}) in total imports of product k of middle-income South American countries (M_{SAkt}) in year t, and $\frac{M^C_{HIkt}}{M_{HIkt}}$ is the share of imports from China of product k in high-income markets (M^C_{HIkt}) in total imports of product k of high-income countries (M_{HIkt}) in year t.[2] It should be noted that we use two different samples of countries to construct our IV because Chinese firms serving high-income markets might systematically differ from those exporting to middle-income countries, leading to different competition levels (Baldwin & Harrigan, 2011; Hallak, 2006).

Our shift-share (or "Bartik") instrument can be considered valid when the instrument is both relevant and exogenous. The relevance condition requires that the IV is correlated with the share of Chinese imports. The correlation between the shares of Chinese imports in the US and the comparable high-income countries at the eight-digit product level is 0.72, while the correlation between the shares of Chinese imports in Mexico and the comparable South American economies is 0.62. These coefficients show a high correlation between the endogenous variables and the IVs. These high correlations can be observed in Figure 3, which shows similar increasing trends for China's average import shares in these markets. Thus, this evidence suggests that the relevance condition is likely valid in this case.

Figure 3: Share of Chinese imports in Mexico, South America, US and high-income countries



Source: UN COMTRADE database. The figure presents the share of imports from China in total imports of Mexico, South America, US, and high-income countries. The group of South American countries includes Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela. The group of high-income countries includes Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom.

[2] We use all countries that meet the corresponding definition and have data available for the full sample period. This implies that the sample of South American countries includes Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela, while the sample of high-income countries includes Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom.

The validity of the exclusion restriction assumption of the shift-share instrument, which is equivalent to the average of a set of shocks (the share of Chinese imports by product and group of countries in our case) weighted by some exposure shares (the shares of product sales in our case), requires the exogeneity of the shocks, the exposure shares, or both depending on the setting. Goldsmith-Pinkham, Sorkin, and Swift (2020) show that, in some research designs, the identification of the shift-share instrument can be based on the exogeneity of the exposure weights. On the other hand, Borusyak, Hull, and Jaravel (2022) provide an econometric framework in which identification follows from the quasi-random assignment of shocks, while the weights are allowed to be endogenous. In our setting, with fixed exposure weights and the inclusion of plant and sector-year fixed effects, a sufficient condition for the validity of our IV is that product-level changes in Chinese exports to other countries be uncorrelated with unobservable shocks to plants with sales concentrated in those products, except those operating through the effect of increased competition.

Table 2 reports the estimates of the effect of Chinese competition on the skill premium in our sample of Mexican manufacturing plants based on equation (2.2.2). In all regressions, the F statistics of the first stage range from 82 to 216, which are well above the conventional threshold of 10.[3] We also reject the null hypothesis of underidentification and weak identification using the Kleibergen-Paap LM statistics and the Kleibergen-Paap Wald F statistics, respectively. These statistics confirm the informativeness of the instrumental variables.

Based on the fixed effects specification in column (1), there is a negative relationship between Chinese competition and the skill premium. The IV specification in column (2) yields a larger negative estimate, which is significant at the 10% level. The result suggests that a one-percentage-point increase in China's market share leads to a decrease by about 0.319% in the wage ratio. Put differently, if a plant has a wage ratio at the median of the skill premium distribution (i.e., 2.34), its wage ratio will decrease to the first quartile of the distribution when facing a one-percentage-point increase in China's import share.[4]

[3] Results of the first-stage regressions are reported in Table D1 in Appendix D.

[4] In Table E4 and Table E5 in Appendix E, we estimate the effect of Chinese competition separately for skilled and unskilled wages. The impact is negative in both cases but statistically significant only in the skilled wage regression. Additionally, we do not find any statistically significant effect of Chinese competition on employment of skilled and unskilled workers and the skill intensity (see Table E1, Table E2, and Table E3 in Appendix E).

Table 2: Impact of Chinese competition on the skill premium

	FE (1)	IV (2)	FE (3)	IV (4)	FE (5)	IV (6)
China share, lag	-0.092	-0.319*	-0.095	-0.488**	-0.096	-0.470**
	(0.072)	(0.179)	(0.073)	(0.207)	(0.084)	(0.214)
China share, lag × Initial TFP			0.003	0.068**		
			(0.011)	(0.032)		
China share, lag × Initial export status					0.013	0.526*
					(0.150)	(0.284)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.449		116.253		154.645
KP Wald F stat		216.449		60.889		97.384

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Next, we take into account that the effect of Chinese competition on the skill premium could vary according to plants' initial characteristics, including productivity and export status. Thus, we interact each of these variables with $China\ share_{i,t-1}$. The results are reported in the last four columns of Table 2. Initially more-productive plants and exporting plants observe a lower decrease in the skill premium when facing tougher foreign competition.[5]

These results are in contrast with those in Utar and Ruiz (2013), who find that Mexican *maquila* plants observe an increase in the relative wages of skilled workers when facing tougher competition from China. The difference in results is due to the difference between *maquila* plants and the plants in our sample. *Maquila* plants export all their products to the US, as such Utar and Ruiz (2013) focus on competition in the US market. In our case, we capture both competition in the US and Mexico markets. In addition, their result is consistent with our finding that initial exporters observe a lower decrease in the skill premium when facing tougher foreign competition (column 6 of Table 2).

[5]Total factor productivity (TFP) at the plant level is estimated following Caselli et al. (2017), which extends the methodology by De Loecker, Goldberg, Khandelwal, and Pavcnik (2016) to a setting in which plants sell in multiple destinations. This methodology controls for potential endogeneity arising from the simultaneity and selection biases due to the correlation between plants' decisions regarding production, inputs and unobserved productivity as well as biases due to the unobserved allocation of inputs within plants and unobserved input prices at the plant level.

To provide an explanation for our results, in the next section we link competition and changes in the skill premium via changes in quality. Supposing firms' product quality depends on the "quality" of skilled workers, then competition leading firms to change their product quality would result in changes in the "quality" of skilled workers, which in turn would result in changes in their relative wage. This is similar to the quality-upgrading mechanism linking exchange-rate shocks and wage inequality in Verhoogen (2008), however our mechanism links competition and the skill premium through quality adjustments at the plant level.

3 A model of competition, quality, and the skill premium

In this section, we propose a simple model to explain the mechanism behind the impact of competition on the skill premium through changes in quality. Our theory draws on four key elements. First, goods are differentiated in quality, and consumers with high income are willing to pay more for products of higher quality, as in Foster et al. (2008). Second, plants are heterogeneous in productivity, and there is a fixed cost of quality upgrading, as in Antoniades (2015). Third, firms require unskilled labour to produce physical output and skilled labour to produce quality. Lastly, the production of higher-quality goods requires higher-quality workers, and higher-quality workers are paid higher wages. In this context, tougher competition leads to quality downgrading by plants, which induces a decline in plants' skill premium.

3.1 Assumptions

3.1.1 Preferences

Consider an economy with L consumers, each supplying one unit of labour. Following Melitz and Ottaviano (2008) and Foster et al. (2008), preferences are defined over a continuum of differentiated goods $i \in \Omega$, and a homogeneous good chosen as a numeraire:

$$U = q_0^c + \alpha \int_{i\in\Omega} q_i^c di + \beta \int_{i\in\Omega} z_i q_i^c di - \frac{1}{2}\gamma \int_{i\in\Omega} (q_i^c)^2 di - \frac{1}{2}\eta \left(\int_{i\in\Omega} q_i^c di\right)^2, \qquad (3.1.1)$$

where q_0^c and q_i^c denote the individual consumption levels of the numeraire good and each variety i, respectively, and z_i refers to the quality of variety i. The utility function captures the consumer's preference for both quantity and quality of variety i. The demand parameters α, β, γ, and η are all positive. The parameters α and η capture the degree of substitution between the differentiated varieties and the numeraire, while the paramter γ indexes the degree of product differentiation between varieties. The parameter β indexes quality valuation.

Assuming that consumers have positive demands for the numeraire good ($q_0^c > 0$), the inverse demand for each variety i is given by

$$p_i = \alpha - \gamma q_i^c + \beta z_i - \eta Q^c \tag{3.1.2}$$

whenever $q_i^c > 0$, where $Q^c = \int_{i\in\Omega} q_i^c di$. Let $\Omega^* \subset \Omega$ be the subset of varieties that are consumed ($q_i^c > 0$). The linear market demand system for variety $i \in \Omega^*$ is:

$$q_i = Lq_i^c = \frac{L}{\gamma}\frac{\alpha\gamma + \eta N\bar{p} - \eta N\beta\bar{z}}{\eta N + \gamma} - \frac{L}{\gamma}p_i + \frac{L\beta}{\gamma}z_i, \tag{3.1.3}$$

where N is the number of consumed varieties in Ω^*, $\bar{p} = 1/N\int_{i\in\Omega^*} p_i di$ is the average price, and $\bar{z} = 1/N\int_{i\in\Omega^*} z_i di$ is the average quality. Equation (3.1.3) implies that after controlling for price, varieties with higher quality have higher market shares.

The inverse market demand is

$$p_i = \frac{\alpha\gamma + \eta N\bar{p} - \eta N\beta\bar{z}}{\eta N + \gamma} - \frac{\gamma}{L}q_i + \beta z_i. \tag{3.1.4}$$

When $q_i = 0$, $p_i = p_{max} = \dfrac{\alpha\gamma + \eta N\bar{p} - \eta N\beta\bar{z}}{\eta N + \gamma}$.

The price elasticity of demand is $\varepsilon_i \equiv \left|\dfrac{\partial q_i}{\partial p_i}\dfrac{p_i}{q_i}\right| = \left[\dfrac{p_{max}}{p_i} - 1 + \beta\dfrac{z_i}{p_i}\right]^{-1}$. A lower average price $\bar{p}$, a higher average quality $\bar{z}$, or a larger number of varieties N induces a decrease in the price bound p_{max} and thus an increase in the price elasticity of demand ε_i at any given p_i and z_i.[6] Therefore, an increase in the number of varieties N is characterised as a tougher competitive environment in our model.[7]

3.1.2 Production technology

The production of the homogeneous good uses the production worker as the only input under constant returns to scale at unit cost and perfect competition. The production technology of the differentiated goods is based on Antoniades (2015). There are $\mathfrak{J}$ firms producing differentiated products under monopolistic competition. Each firm has a negligible impact on the market outcome, and the interaction between any two firms is zero. However, aggregate market conditions (here, average price, average quality across firms, and the total number of varieties) affect any single firm.

All firms pay a common fixed cost f_E to enter the market, and then they draw a cost parameter a. The cumulative distribution of a is $G(a)$ with density $g(a)$ and support on $[a_0, a_M]$.

[6] From equation (3.1.2), we have $\bar{p} = \alpha - \gamma\bar{q^c} + \beta\bar{z} - \eta Q^c$. Thus, $\bar{p} - \beta\bar{z} - \alpha = -(\gamma\bar{q^c} + \eta Q^c)$, which is negative, and $\dfrac{\partial p_{max}}{\partial N} = \dfrac{\eta\gamma(\bar{p} - \beta\bar{z} - \alpha)}{(\gamma + \eta N)^2} < 0$.

[7] Melitz and Ottaviano (2008) also use the number of varieties as a measure of competition in their model.

Firms with low productivity exit the market. The remaining firms maximise profits by taking the number of firms N, the average price $\bar{p}$, and the average level of quality $\bar{z}$ as given. Firms also choose the optimal level of quality.

Firms require production labour (unskilled labour) to produce physical output and non-production labour (skilled labour) to produce quality. Production workers are homogeneous, while non-production workers are heterogeneous in skills. The production of one unit of physical output at quality level z requires one unit of production labour and one unit of non-production labour with skill level z. A firm's marginal cost to produce a physical unit of good i at the quality level z_i is: $c_i(z_i) = a_i w_u + w_s(z_i)$, where w_u is the wage of production workers and $w_s(z_i)$ is the wage of non-production workers of skill level z_i. We assume that the wage of skilled workers is a convex function of quality that satisfies $\frac{\partial w_s(z)}{\partial z} > 0$ and $\frac{\partial^2 w_s(z)}{\partial z^2} \geq 0$.[8] The production of quality requires higher quality inputs that are more costly to purchase. We discuss the distributional assumptions necessary for this to be an equilibrium outcome when we introduce labour market clearing.

The cost function of a surviving firm i is given by

$$TC_i = q_i a_i w_u + q_i w_s(z_i) + \theta z_i^2. \tag{3.1.5}$$

The first term captures the cost of production labour required to produce physical output. The second term accounts for the fact that quality upgrades require skilled labour and raise the marginal cost of production. As in Antoniades (2015), the third term indexes the fixed cost of quality upgrading that is invariant to output and convex. Quality comes from innovation, and this innovation increases with the level of quality upgrade but not with quantity. The parameter θ captures country- or industry- specific differences in the ability to innovate.

There are two striking differences between our model and the model in Antoniades (2015). First, we introduce two factors of production in our model: production workers, who are homogeneous in skills, and non-production workers, who are heterogeneous in skills. Second, product quality is produced using non-production workers. Therefore, the wages of skilled workers are endogenous to the quality levels chosen by firms.

For a given output level, firms choose a price to minimise the cost function. Let c_D be the marginal cost cutoff between firms that produce and firms that exit. A firm with marginal cost c_D earns a zero profit and its demand $q(c_D)$ is driven to 0. Thus $c_D = p_{max}$. We can express all

[8] The property of convexity in skills in the wage function is a common characteristic in models of job assignment and distribution of income (Antràs, Garicano, & Rossi-Hansberg, 2006; Garicano & Rossi-Hansberg, 2006; Saint-Paul, 2001; Sattinger, 1993).

performance measures as functions of the marginal cost cutoff, c_D, and quality, z:

$$p(c,z) = \frac{1}{2}\Big[(c_D + aw_u) + \big(\beta z + w_s(z)\big)\Big] \tag{3.1.6}$$

$$q(c,z) = \frac{L}{2\gamma}\Big[(c_D - aw_u) + \big(\beta z - w_s(z)\big)\Big] \tag{3.1.7}$$

$$\pi(c,z) = \frac{L}{4\gamma}\Big[(c_D - aw_u) + \big(\beta z - w_s(z)\big)\Big]^2 - \theta z^2. \tag{3.1.8}$$

Firms, then, choose quality in order to maximise the profit function in equation (3.1.8):

$$\frac{\partial \pi}{\partial z} = \frac{L}{2\gamma}\Big(\beta - \frac{\partial w_s(z)}{\partial z}\Big)\Big(c_D - aw_u + \beta z - w_s(z)\Big) - 2\theta z = 0. \tag{3.1.9}$$

To ensure that there is an interior solution to the profit maximisation problem, we assume that $\dfrac{\partial^2 \pi}{\partial z^2} < 0$.

3.1.3 Labour market clearing

Any individual is endowed with one unit of labour, either production or non-production. Each non-production worker is endowed with a skill level z with distribution $H(z)$, density function $h(z)$, and support on $[0, z_M]$. A non-production worker with skill level z will work for a firm producing products at the quality level z.

Since production workers are homogeneous, we assume that the outside numeraire good uses production workers one-for-one, and hence the wage of production workers is normalised to 1.

We close the model by imposing a market clearing for non-production workers, which is guaranteed when supply equals demand for every skill level of workers:

$$\int_0^{z_M} h(z)dz = \int_{a_0}^{a_M} q(a)g(a)da, \tag{3.1.10}$$

where q is the output quantity of a firm with cost parameter a, $q(a) = \dfrac{L}{2\gamma}\Big[(c_D - aw_u) + \big(\beta z - w_s(z)\big)\Big]$. The left-hand side of equation (3.1.10) is the supply of non-production workers between 0 and z_M. The right-hand side is the demand for non-production workers by firms. A firm with marginal cost parameter a will produce q output at quality level z, and thus demand q workers at skill level z.

Taking the total differential of the first order condition in (3.1.9) with respect to quality z and the marginal cost parameter a gives: $\dfrac{\partial^2 \pi}{\partial z^2}dz + \dfrac{\partial^2 \pi}{\partial z \partial a}da = 0$. We can notice that $\dfrac{\partial^2 \pi}{\partial z^2} < 0$ and

$\frac{\partial^2 \pi}{\partial z \partial a} = -\frac{L w_u}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right) < 0$. Therefore, $\frac{dz}{da} = -\frac{\partial^2 \pi}{\partial z \partial a} \Big/ \frac{\partial^2 \pi}{\partial z^2}$ is also negative, which implies that more productive firms produce varieties of higher quality.

Since there is a one-to-one relationship between z and the cost parameter a, we can express quality z as a decreasing function of the cost parameter a, $z = f(a)$ where $f(a)$ is a decreasing function of a, $f'(a) < 0$. The demand for non-production workers becomes:

$$\int_{a_0}^{a_M} q(a)g(a)da = \int_{m(z_M)}^{m(0)} q(m(z))g(m(z))d(m(z)),$$

where $q(m(z)) = \frac{L}{2\gamma}\Big[(c_D - m(z)w_u) + \big(\beta z - w_s(z)\big)\Big]$, and $m(z)$ is the inverse function of f.[9]

Therefore, the labour market clearing condition can be rewritten as follows:

$$\int_{0}^{z_M} h(z)dz = \int_{m(z_M)}^{m(0)} q(m(z))g(m(z))d(m(z)). \tag{3.1.11}$$

Differentiating both side of (3.1.11) with respect to z_M, we get:

$$h(z_M) = -q(m(z_M))g(m(z_M))m'(z_M), \tag{3.1.12}$$

where

$$m'(z) = \frac{da}{dz} = -\frac{\frac{\partial^2 \pi}{\partial z^2}}{\frac{\partial^2 \pi}{\partial z \partial a}} = -\frac{-\frac{L}{2\gamma}\frac{\partial^2 w_s(z)}{\partial z^2}q + \frac{L}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)^2 - 2\theta}{-\frac{L w_u}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)}. \tag{3.1.13}$$

Substituting (3.1.13) into (3.1.12) and solving for $\frac{\partial^2 w_s(z)}{\partial z^2}$, we get:

$$\frac{\partial^2 w_s(z)}{\partial z^2} = \frac{1}{q(z)}\left[\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)\left(\frac{h(z)w_u}{q(m(z))g(m(z))} + \beta - \frac{\partial w_s(z)}{\partial z}\right) - \frac{4\theta\gamma}{L}\right]. \tag{3.1.14}$$

[9] The distribution of a has support on $[a_0, a_M]$; thereby, $z = f(a) \in [f(a_M), f(a_0)]$, where $f(a_M) = 0$ and $f(a_0) = z_M$. Therefore, we can write $a = f^{-1}(z) = m(z)$, where $m(z)$ is decreasing in z, $m'(z) = \frac{\partial a}{\partial z} < 0$. As $z \in [0, z_M]$, $a \in [m(z_M), m(0)]$.

Also substituting (3.1.13) into (3.1.12) and rearranging, we get:

$$\begin{aligned}&\Big(\frac{\partial w_s(z)}{\partial z}\Big)^2 - \Big(2\beta + \frac{h(z)w_u}{q(m(z))g(m(z))}\Big)\frac{\partial w_s(z)}{\partial z} + \\ &- \Big(\frac{4\theta\gamma}{L} + \frac{\partial^2 w_s(z)}{\partial z^2}q(z) - \beta\Big(\beta + \frac{h(z)w_u}{q(m(z))g(m(z))}\Big)\Big) = 0.\end{aligned} \tag{3.1.15}$$

This implies that the second order derivative of the skilled wage function with respect to quality is non-negative $\Big(\frac{\partial^2 w_s(z)}{\partial z^2} \geq 0\Big)$ when

$$\Big(\beta - \frac{\partial w_s(z)}{\partial z}\Big)\Big(\frac{h(z)w_u}{q(m(z))g(m(z))} + \beta - \frac{\partial w_s(z)}{\partial z}\Big) - \frac{4\theta\gamma}{L} \geq 0.$$

In addition, the first order derivative of the skilled wage function with respect to quality is positive $\Big(\frac{\partial w_s(z)}{\partial z} > 0\Big)$ when equation (3.1.15) has a positive solution. This is ensured as long as

$$\Big(2\beta + \frac{h(z)w_u}{q(m(z))g(m(z))}\Big)^2 + 4\Big[\frac{4\theta\gamma}{L} + \frac{\partial^2 w_s(z)}{\partial z^2}q(z) - \beta\Big(\beta + \frac{h(z)w_u}{q(m(z))g(m(z))}\Big)\Big] \geq 0.$$

These conditions ensure that the two assumptions on the first and second order derivatives of the skilled wage function with respect to quality in the production technology section are satisfied.

3.2 Model predictions

Prediction 1: *Tougher competition leads to quality downgrading, which in turn induces a decrease in the skill premium.*

We begin our analysis of the impact of competition on quality upgrading by calculating the total differential for $\frac{\partial \pi}{\partial z}$: $\frac{\partial^2 \pi}{\partial z^2}dz + \frac{\partial^2 \pi}{\partial z \partial N}dN = 0$. Therefore,

$$\frac{dz}{dN} = -\frac{\frac{\partial^2 \pi}{\partial z \partial N}}{\frac{\partial^2 \pi}{\partial z^2}} = -\frac{\frac{L}{2\gamma}\Big(\beta - \frac{\partial w_s(z)}{\partial z}\Big)\frac{\eta\gamma(\bar{p} - \beta\bar{z} - \alpha)}{(\eta N + \gamma)^2}}{\frac{\partial^2 \pi}{\partial z^2}}, \tag{3.2.1}$$

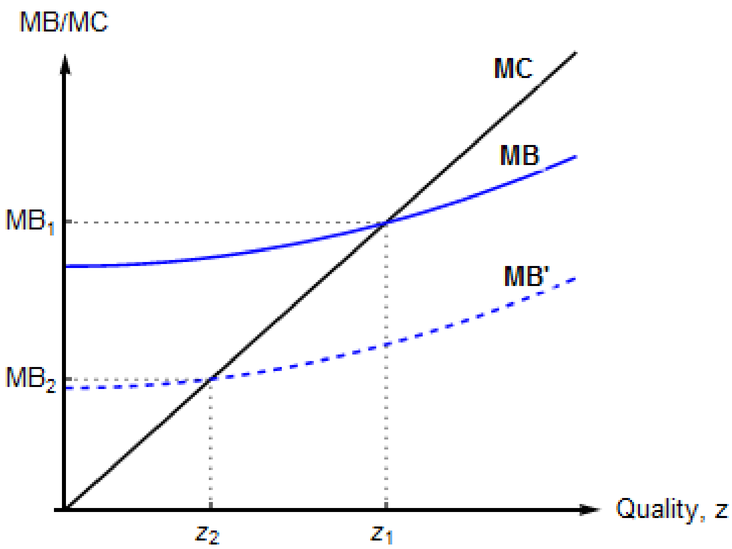
which is negative as we assume that $\frac{\partial^2 \pi}{\partial z^2} < 0$ and $\frac{\partial c_D}{\partial N} = \frac{\eta\gamma(\bar{p} - \beta\bar{z} - \alpha)}{(\eta N + \gamma)^2} < 0$.[10] Thus, in this setup, tougher competition leads to quality downgrading.

[10] $\beta - \frac{\partial w_s(z)}{\partial z} > 0$ to ensure that the first order condition in equation (3.1.9) is satisfied.

In the first order condition in equation (3.1.9), the marginal benefit of quality upgrading is $MB = \frac{L}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)\left(c_D - aw_u + \beta z - w_s(z)\right)$, while the marginal cost of quality upgrading is $MC = 2\theta z$. As the marginal cost of quality upgrading (MC) does not depend on the number of firms, when more firms enter the market (N increases), MC does not change. However, market toughness lowers the cost cutoff (c_D) between the firms that operate in the market and those that exit. This implies that the market becomes more elastic and competitive pressure is higher. Thus, a decrease in the cost cutoff associated with tougher competition (larger N) induces a decline in the marginal benefit MB and, in turn, a lower incentive for firms to invest in quality upgrading.

This mechanism is illustrated in Figure 4. When N increases, the marginal cost line remains the same, while the marginal benefit line shifts down from MB to MB'. Therefore, the new optimal quality z_2 is lower than the old one z_1.[11]

Figure 4: Competition and product quality



Notes: The figure above illustrates how market toughness affects quality upgrading. As the number of firms in the market rises, the marginal cost of quality upgrading (MC) does not change, while the marginal benefit shifts down from MB to MB'. There is less incentive for firms to invest in quality upgrading. Consequently, the new optimal quality z_2 is lower than the old optimal quality z_1.

The decrease in quality implies that firms will hire non-production workers of lower skill

[11] In Aghion et al. (2018), there is also a negative effect of competition on innovation incentives. In their paper, an increase in demand for products produced by export firms in the destination market will have two main effects on exporting firms' innovation incentives. First, growth in demand will expand the market for exports for these firms, which increases the size of innovation rents and thus increases exporting firms' incentives to invest more in innovation (i.e., the "direct market size effect"). On the other hand, the rise in demand also attracts new firms into the destination market, which will raise competition for exporters in the market and trigger a decrease in firm output and market share. All firms respond by reducing innovation, but the reduction in innovation is most pronounced for high-cost firms (i.e., the "competition effect"). This "competition effect" is caused by lower sales and consequently higher costs, which is different from our model where the marginal cost is assumed to be constant.

levels to produce products of lower quality, which leads to a decline in the skill premium since the wage of production workers is normalised to 1.

Prediction 2: *The negative effect of competition on product quality is likely to be weaker in higher-income destinations.*

The literature on product quality has found that quality valuation is increasing in income ($\beta'(y^d) > 0$, where y^d refers to income in destination d) since consumers in wealthier countries value quality more than those in poor countries (Hallak, 2006). Thus, the taste parameter β can be used to classify countries as high- and low-income.

We rewrite equation (3.2.1) in full, as follows:

$$\frac{\partial z}{\partial N} = \frac{-\frac{L}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)\frac{\eta\gamma(\bar{p}-\beta\bar{z}-\alpha)}{(\eta N+\gamma)^2}}{-\frac{L}{2\gamma}\frac{\partial^2 w_s(z)}{\partial z^2}\left(\frac{\alpha\gamma+\eta N\bar{p}-\eta N\beta\bar{z}}{\eta N+\gamma} - aw_u + \beta z - w_s(z)\right) + \frac{L}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)^2 - 2\theta}. \tag{3.2.2}$$

Differentiating equation (3.2.2) with respect to β, we have:

$$\begin{aligned}\frac{\partial^2 z}{\partial N\partial\beta} = & \frac{\frac{L\eta}{2(\eta N+\gamma)^2} * \left[-(\bar{p}-\beta\bar{z}-\alpha) + \bar{z}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)\right] * \frac{\partial^2\pi}{\partial z^2}}{\left(\frac{\partial^2\pi}{\partial z^2}\right)^2} \\ & + \frac{\frac{L^2\eta}{2\gamma(\eta N+\gamma)^2} * \left(\beta - \frac{\partial w_s(z)}{\partial z}\right)^2 * (\bar{p}-\beta\bar{z}-\alpha)}{\left(\frac{\partial^2\pi}{\partial z^2}\right)^2} \\ & + \frac{\frac{L^2\eta}{4\gamma(\eta N+\gamma)^2} * \left(\beta - \frac{\partial w_s(z)}{\partial z}\right) * (\bar{p}-\beta\bar{z}-\alpha) * \frac{\partial^2 w_s(z)}{\partial z^2} * \left(\frac{\eta N\bar{z}}{\eta N+\gamma} - z\right)}{\left(\frac{\partial^2\pi}{\partial z^2}\right)^2}.\end{aligned} \tag{3.2.3}$$

Given that $\beta - \frac{\partial w_s(z)}{\partial z} > 0$, $\bar{p} - \beta\bar{z} - \alpha < 0$, $\frac{\partial^2\pi}{\partial z^2} < 0$, the first two terms in equation (3.2.3) are negative. On the other hand, given that $\frac{\partial^2 w_s(z)}{\partial z^2} \geq 0$, the sign of the last term is opposite to the sign of $\left(\frac{\eta N\bar{z}}{\eta N+\gamma} - z\right)$. Therefore, $\frac{\partial^2 z}{\partial N\partial\beta}$ is more likely to be positive if $\frac{\eta N\bar{z}}{\eta N+\gamma} - z < 0$, i.e., when $\frac{\eta N\bar{z}}{\eta N+\gamma} < z$, which is more likely to occur in high-income markets since firms usually export higher quality goods to richer nations (Bastos & Silva, 2008; Hallak, 2006; Verhoogen, 2008). This means $\frac{\partial z}{\partial N}$ is likely to be less negative or more positive for advanced countries because the negative effect of competition on product quality tends to be weaker in high-income markets than in low-income ones.

4 Main empirical analysis: Effect on product quality

Our model in the previous section predicts that firms downgrade product quality when facing tougher competition. To downgrade quality, firms hire non-production workers of lower skills and, thus, the skill premium decreases. Indeed, in Section 2.2, we found that Mexican plants decrease the skill premium when facing tougher competition from Chinese plants.

Next, we empirically analyse Mexican plants' response to Chinese competition with respect to product quality to test the predictions of our model and, thus, the mechanism behind the decrease in the skill premium. To recover quality at the product-plant-market level, we use the framework developed by Khandelwal et al. (2013). Then, we investigate the effect of Chinese competition on the product quality of Mexican plants based on an IV approach similar to that described in Section 2.2 but at the plant-product-market level.

4.1 Quality estimation

We estimate a measure of product quality following the methodology in Khandelwal et al. (2013). The intuition behind this method is that conditional on price a variety with a higher market share is assigned higher quality. Within each product category, we treat each product-plant-market as a distinct variety. The quality for each product-plant-market-year observation can be estimated as the residual from the following OLS regression:

$$lnq_{ikdt} + \sigma_{kd} lnp_{ikdt} = \alpha_k + \alpha_{dt} + \varepsilon_{ikdt}, \tag{4.1.1}$$

where the market-year fixed effects, α_{dt}, control for the destination country's income and price index, and the product fixed effects, α_k, capture differences in units of measurements of prices and quantities across product categories. We assume a specific value of the demand elasticity σ_{kd} for product k in market d. Our measures of σ_{kd} at the product-market level are taken from Broda and Weinstein (2006) for the US and Broda, Greenfield, and Weinstein (2017) for Mexico. Imposing an estimate of the elasticity of substitution taken from the literature allows us to avoid having to estimate the demand for each good before inferring quality. Estimated quality is then given by $ln(\hat{z}_{ikdt}) = \hat{\varepsilon}_{ikdt}$.

To estimate product quality, we use the same sample of plants used in the skill premium regressions. The summary statistics for estimated product quality by sector and market are reported in Table 3.[12]

Table 3: Summary statistics for quality, by sector and market

Sector	No. Plants	Domestic market		Foreign market	
		Mean	Median	Mean	Median
Food, beverages and tobacco	906	0.884	0.297	-8.684	-3.578
Textile, wearing apparel and leather	744	0.301	0.099	-1.513	0.358
Wood and wood products	178	-0.433	-0.138	3.787	2.175
Paper and paper products	362	0.713	0.612	-6.787	-6.977
Chemicals, petroleum, coal products	875	0.634	-0.034	-2.642	0.804
Non-metallic mineral products	327	-0.294	0.006	1.554	1.878
Basic metal products	118	-1.030	-0.339	2.042	0.560
Machinery and equipment	914	-2.381	-0.525	7.101	1.199
Total	4424	0	0.027	0	0.507

Notes: The table reports the number of plants in each sector, and the mean and median of estimated quality by sector and market. Product quality at the product-plant-market-year level is estimated using the method in Khandelwal et al. (2013). The table trims observations with skill premiums that are below the 1st and above the 99th percentiles.

4.2 Empirical results

We examine the effect of Chinese competition on product quality at the product-plant-market level using the following specification:

$$\hat{\varepsilon}_{ikdt} = \beta China\ share_{kd,t-1} + \alpha_{ikd} + \alpha_{rt} + \alpha_{st} + e_{ikdt}. \tag{4.2.1}$$

Given that our dependent variable is now at the product-plant-market-year level, we now control for product-plant-market fixed effects (α_{ikd}). The inclusion of the product-plant-market fixed effects not only captures varieties' characteristics but also ensures that the estimation exploits the within variation. To mitigate measurement error stemming from the estimation of quality, we trim observations with estimated quality that are below the 5th and above the 95th percentiles of quality within each sector and in both domestic and export markets.

The measure of Chinese competition is calculated at the product-market-year level as follows

$$China\ share_{kdt} = \frac{M^C_{dkt}}{M_{dkt}}. \tag{4.2.2}$$

We follow the same strategy as in Section 2.2 to instrument for $China\ share_{kdt}$. However, as the shocks and the regression observations are at the same level, we do not need to aggregate our measure of Chinese competition and, thus, we do not need to use weights. This implies that now there is no issue of endogeneity coming from the weights of our IV.

[12]Detailed summary statistics for estimated product quality can be found in Appendix C.

The effect of Chinese competition on product quality is reported in Table 4.[13] The first two columns report the average effect across the domestic and exports markets, as in **Prediction 1** of our model. The last two columns shows how the results vary across the domestic and foreign markets, as in **Prediction 2** of our model. *Foreign* is a dummy taking a value of one if a product is sold in the foreign market and zero otherwise. Notice that in our case the foreign market is represented by the US, a richer economy than Mexico.

Table 4: Impact of Chinese competition on product quality

	Baseline		Market	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
China share, lag	-1.350***	-5.147***	-1.693***	-5.201***
	(0.420)	(1.363)	(0.483)	(1.365)
China share, lag × Foreign			1.785***	4.556***
			(0.554)	(1.103)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	102467	102423	102467	102423
KP LM stat		104.275		110.912
KP Wald F stat		96.828		54.412

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

In line with the predictions of our model, plants downgrade product quality in response to higher competitive pressure from China. In addition, the coefficients of the interaction term in columns (3) and (4) are positive and statistically significant. This implies that, when facing tougher foreign competition, plants downgrade product quality, but less so for products sold in the high-income foreign market compared with products sold in the domestic market. The effects are stronger in the IV regressions in columns (2) and (4). In particular, a one-percentage-point increase in China's import share leads plants to downgrade quality by about 5.1%, but this decrease disappears for products sold in the rich foreign market.

These results are consistent with the negative effect of tougher competition on the skill premium and the heterogeneity in the effect according to the export status reported in Section

[13] Results of the first-stage regressions are reported in Table D2 in Appendix D.

2.2 above. These results are also consistent with the predictions of our model. Mexican plants respond to increasing competition from China by downgrading their product quality due to a reduction in the innovation rent. Therefore, they hire white-collar workers of lower skill levels, which in turn induces a decrease in the skill premium.[14]

5 Robustness analysis

In this section, we check the robustness of the empirical results to different controls, including total factor productivity at the plant level, exchange rate shocks, and tariffs.[15]

A potential concern is that shocks at the plant level correlated with the skill premium, quality and competition from China might bias our results. Thus, we control for TFP at the plant level in Table F1 and Table F11. In addition, 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 (Caselli et al., 2017). This allows us to control for shocks at the product-plant level that are potentially correlated with product quality and competition from China. The results are presented in Table F12. All our results are robust to controlling for either productivity or marginal cost.

Verhoogen (2008) finds that Mexican firms respond to exchange-rate shocks by upgrading product quality and, thus, increasing within-industry wage inequality. To eliminate the potential concern that exchange rate shocks may bias our results and to remove a possible differential effect of the 1994 peso crisis, we control for the interactions between the exchange rate of the US dollar to the Mexican peso and the share of exports in total sales, the share of imports in materials, and the share of imports in machinery and equipment investment (Table F2 and Table F13).[16] The shares of exports and imports are fixed at the values in the first year available. Our results do not change significantly when we include the interactions between the exchange rate and the shares of exports and imports in our regressions.

Another concern is that the effect of Chinese competition might be biased because of the tariff reductions following the North American Free Trade Agreement in 1994. In Table F3 and Table F14 we control for tariffs imposed on imports from Mexico by the US at the product

[14]Table E4 and Table E5 in Appendix E also support the predictions of our model as they show that the impact of Chinese competition has been mainly on the wage of blue-collar workers rather than that of white-collar workers.

[15]We also estimate equation (2.2.2) using China's import share in the domestic market and China's import share in the foreign market separately (see Table F6). We estimate the same equation for a subsample of initial non-exporters (see Table F7) and for a subsample of initial exporters (see Table F8). Our results remain robust to all these robustness checks, which are all presented in Appendix F.

[16]At the macro level, the effect of exchange-rate shocks is captured by the sector-year fixed effects in our regressions. The use of exchange-rate shocks at the macro level is common in the literature on the effect of exchange-rate shocks on wage inequality (Amiti & Cameron, 2012; Araújo & Paz, 2014).

level, while in Table F4 and Table F15 we include tariffs imposed on imports from the US by the Mexican government. In addition, in Table F5 and Table F16 we include intermediate input tariffs, which are computed by weighting tariffs imposed on goods from the US by the Mexican government by their input cost shares.[17] Our results remain robust to all these robustness checks.

In our regressions, we address the concern regarding measurement error by trimming the bottom and top 1% of the skill premium distribution and the bottom and top 5% of the quality distribution within each sector and market. We obtain similar results when using the full sample (Table F9 and Table F18). We also check for the robustness of the results by using quality estimated based on a sample that excludes the bottom and top 5% of plants in terms of sales within each sector and market (Table F17). Our results are robust to the use of this different sample.

6 Conclusion

We analyse the impact of the rising competition from Chinese imports on the skill premium of Mexican plants in both domestic and foreign markets using detailed information on Mexican manufacturing plants. Our results suggest that the rise of China leads to a reduction in the skill premium, but less so for exporting plants.

We propose a simple model to explain the mechanism behind our empirical findings. In our model of heterogeneous plants and quality differentiation, more productive plants produce higher-quality goods than less productive plants. Plants pay higher wages to hire higher-quality non-production workers to produce higher-quality products. The model predicts that an increase in the number of varieties, i.e., a tougher competitive environment, leads firms to downgrade their product quality. As a consequence, firms hire lower-quality non-production labour and pay lower wages, which decreases the wage difference between non-production and production workers.

Employing the methodology developed by Khandelwal et al. (2013), we estimate product quality at the plant-product-market level and use the estimated quality to empirically investigate the predictions of our model. We provide strong evidence that Mexican plants downgrade the quality of their products in response to increasing competition from China. This effect is more pronounced for products sold in the (lower-income) domestic market. Thus, the empirical results showing a decrease in product quality and the skill premium following rising Chinese competition are consistent with the predictions of our model. These

[17] Tariff data are taken from the United Nations Trade Analysis and Information System (TRAINS) database. The data are measured at the six-digit HS level (HS6, 1992 version). We refer to Appendix H for more information on tariff data and the construction of intermediate input tariffs.

results may contrast with others from other countries because Mexico is a middle-income country, while we expect the results to be different in high-income countries based on our model. Thus, a comparative analysis across different countries to study in more detail the heterogeneous effects is an avenue for future research.

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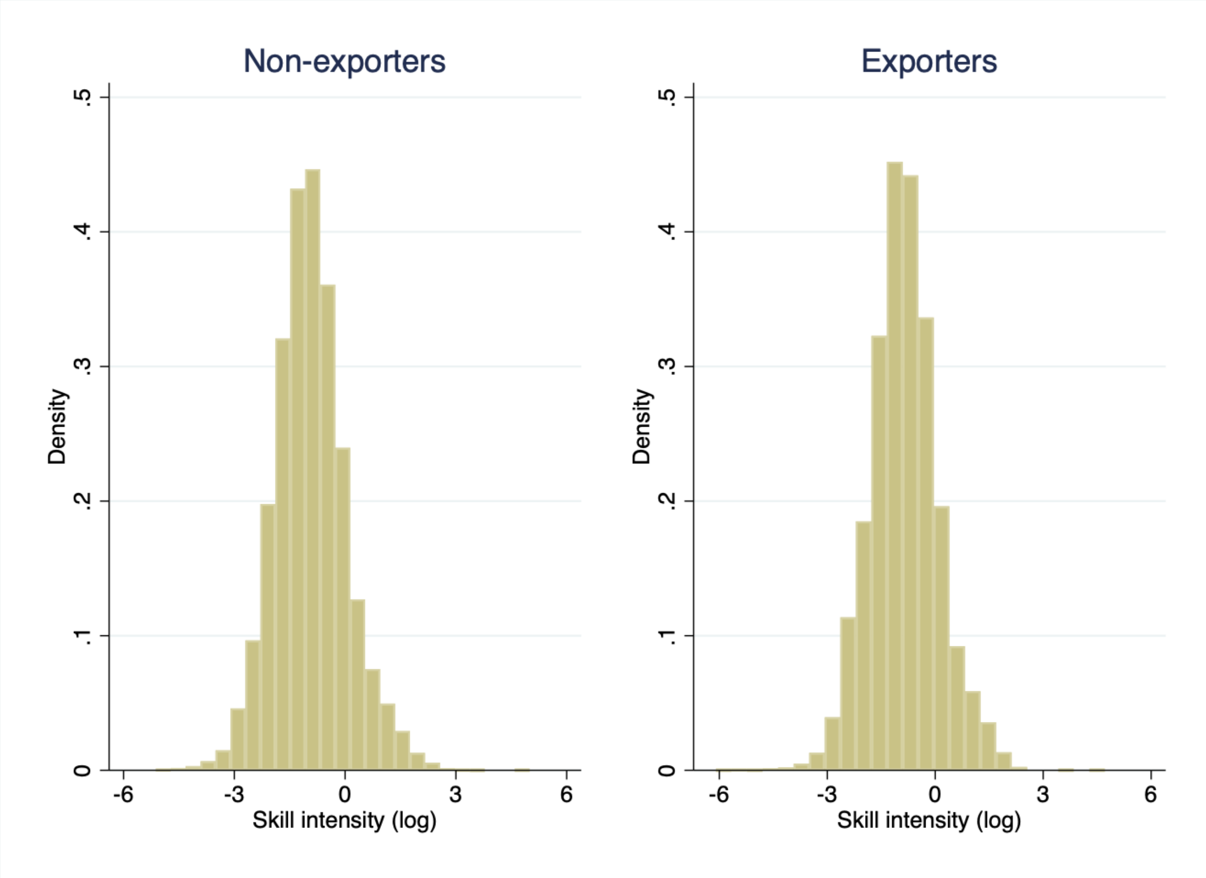
Appendix

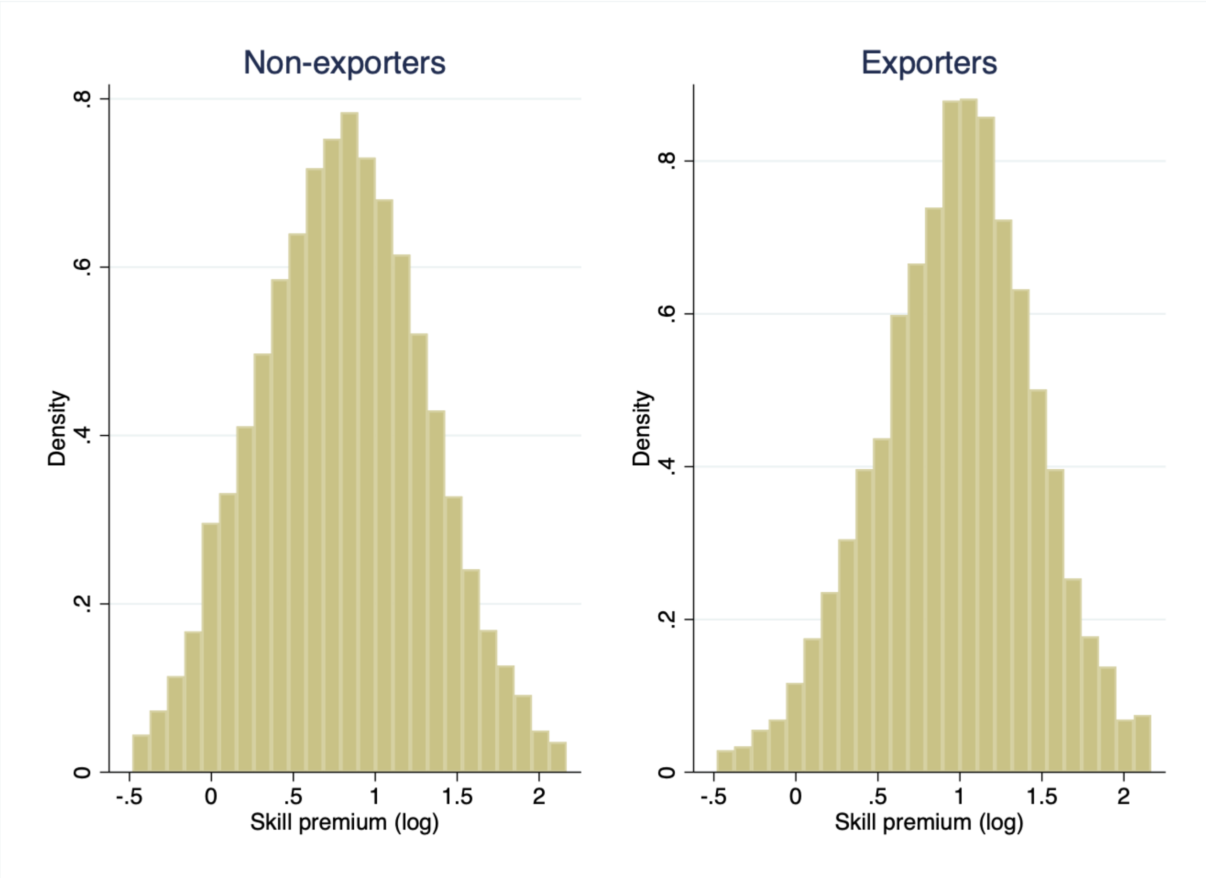
A Distributions of skill intensity and skill premium

Figure A1: Skill intensity distributions



Source: INEGI database. Plants are split into exporters and non-exporters on the basis of their first year available in the sample. The skill intensity is defined as the white-collar to blue-collar employment ratio.

Figure A2: Skill premium distributions



Source: INEGI database. Plants are split into exporters and non-exporters on the basis of their first year available in the sample. The skill premium is defined as the white-collar to blue-collar wage ratio.

B Additional predictions from the model

Prediction 3: *A firm with lower cost parameter a produces a variety of higher quality.*

$$\frac{dz}{da} = -\frac{\frac{\partial^2 \pi}{\partial z \partial a}}{\frac{\partial^2 \pi}{\partial z^2}} = \frac{\frac{L w_u}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)}{\frac{\partial^2 \pi}{\partial z^2}} < 0. \tag{B1}$$

This result is consistent with recent theoretical and empirical works showing that more productive firms produce higher quality goods (Verhoogen, 2008; Antoniades, 2015; Bastos & Silva, 2008; Baldwin & Harrigan, 2011). This prediction is also confirmed by the results in the last column in table C1 and table C4 in the next section.

Prediction 4: *Product quality is usually higher in higher-income destinations.*

$$\frac{dz}{d\beta} = -\frac{\frac{\partial^2 \pi}{\partial z \partial \beta}}{\frac{\partial^2 \pi}{\partial z^2}} = -\frac{\frac{L}{2\gamma}(c_D - aw_u + (\beta z - w_s(z))) + \frac{L}{2\gamma}\left(\beta - \frac{\partial w_s(z)}{\partial z}\right)\left(z - \frac{\eta N \bar{z}}{\eta N + \gamma}\right)}{\frac{\partial^2 \pi}{\partial z^2}}. \quad \text{(B2)}$$

This turns out that $\frac{dz}{d\beta}$ is positive for $\left(z - \frac{\eta N \bar{z}}{\eta N + \gamma}\right) \geq 0$, i.e. goods in the upper distribution of the product quality. If $\left(z - \frac{\eta N \bar{z}}{\eta N + \gamma}\right) < 0$, the sign of $\frac{dz}{d\beta}$ is uncertain. This implies that goods in advanced markets are usually associated with higher quality. This result accords with theoretical and empirical research finding that consumers in richer countries value quality more than those in developing countries (Verhoogen, 2008; Hallak, 2006; Bastos & Silva, 2008).

C Summary statistics on estimated quality

Tables C1, C2, C3, and C4 present summary statistics on estimated product quality.

Table C1: Summary statistics on product quality

	Price	Export share	TFP
1994	0.403***	0.001***	0.011***
	(0.081)	(0.000)	(0.004)
1995	0.575***	0.002***	0.018***
	(0.113)	(0.000)	(0.004)
1996	-0.020	0.002***	0.015***
	(0.221)	(0.000)	(0.004)
1997	-0.029	0.003***	0.012***
	(0.215)	(0.000)	(0.003)
1998	0.315	0.003***	0.012***
	(0.377)	(0.000)	(0.004)
1999	0.096	0.002***	0.014***
	(0.425)	(0.000)	(0.004)
2000	-0.383	0.002***	0.017***
	(0.514)	(0.000)	(0.004)
2001	-0.021	0.003***	0.020***
	(0.536)	(0.000)	(0.004)
2002	-0.126	0.003***	0.017***
	(0.593)	(0.000)	(0.004)
2003	-0.263	0.002***	0.016***
	(0.643)	(0.000)	(0.004)
2004	-0.047	0.002***	0.013***
	(0.609)	(0.000)	(0.004)
2005	0.601	0.002***	0.014***
	(0.506)	(0.000)	(0.004)
2006	0.325	0.003***	0.013***
	(0.965)	(0.000)	(0.004)
2007	0.947	0.003***	0.007
	(0.768)	(0.000)	(0.004)

Notes: The table reports results from fixed-effect regressions of price, export share, and total factor productivity (TFP) on product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. In these regressions, we control for six-digit industry fixed effects. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors are shown in parentheses. ** and *** indicate coefficients significantly different from zero at the 5% and 1% level, respectively.

In table C1, we estimate fixed-effect regressions of price, export share, and total factor productivity on product quality for each year, controlling for six-digit industry fixed effects α_{s_6t}:

$$y_{ikd} = \beta \hat{\varepsilon}_{ikd} + \alpha_{s_6t} + e_{ikd},$$

where y_{ikd} refers to price/ export share/ total factor productivity (TFP). The results show positive correlations between export share and quality and between TFP and quality. These positive correlations are confirmed in tables C3 and C4.

In tables C2, C3, and C4, we estimate fixed-effect regressions of price/ export share/ TFP on a dummy variable containing four quantiles based on product quality distribution within each six-digit industry and year for each year, controlling for six-digit industry fixed effects:

$$y_{ikd} = \beta quartile_{ikd} + \alpha_{s_6 t} + e_{ikd},$$

where y_{ikd} refers to price/ export share/ total factor productivity. We divide product quality distribution within each six-digit industry and year into quartiles and assign a value to $quartile_{ikd}$ based on whether quality of product ikd belongs to the first, second, third, or fourth quartile. A higher coefficient for higher quartile implies a positive correlation between quality and y_{ikd}.

Table C2: Product quality and price

	2nd quartile	3rd quartile	4th quartile
1994	1.314	4.421	4.667
1995	2.635	4.660	9.143
1996	0.280	2.165	5.196
1997	-0.218	1.133	6.820
1998	6.408	15.324	15.451
1999	6.388	15.692	16.107
2000	0.396	16.611	12.527
2001	1.693	17.948	16.301
2002	3.415	19.973	17.733
2003	2.776	22.435	15.425
2004	15.943	17.937	20.257
2005	-0.222	14.351	17.455
2006	15.142	30.162	22.142
2007	23.074	19.399	23.067

Notes: The table reports results from fixed-effect regressions of price on a dummy variable containing four quantiles based on product quality distribution within each six-digit industry and year. In these regressions, we control for six-digit industry fixed effects. Quality is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets.

Table C3: Product quality and export share

	2nd quartile	3rd quartile	4th quartile
1994	-0.001	0.001	0.024
1995	-0.001	-0.001	0.030
1996	-0.005	0.003	0.049
1997	-0.005	0.003	0.054
1998	-0.009	0.002	0.055
1999	-0.007	0.002	0.050
2000	-0.007	-0.002	0.053
2001	-0.009	-0.001	0.057
2002	-0.009	-0.000	0.059
2003	-0.007	0.000	0.058
2004	-0.003	0.004	0.061
2005	-0.006	0.002	0.061
2006	-0.004	0.010	0.067
2007	0.000	0.008	0.066

Notes: The table reports results from fixed-effect regressions of export share on a dummy variable containing four quantiles based on product quality distribution within each six-digit industry and year. In these regressions, we control for six-digit industry fixed effects. Quality is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets.

Table C4: Product quality and TFP

	2nd quartile	3rd quartile	4th quartile
1994	-0.020	0.196	0.358
1995	0.085	0.313	0.489
1996	0.163	0.355	0.547
1997	0.183	0.358	0.510
1998	0.166	0.292	0.427
1999	0.178	0.327	0.512
2000	0.181	0.396	0.453
2001	0.244	0.485	0.503
2002	0.175	0.422	0.503
2003	0.222	0.388	0.542
2004	0.179	0.385	0.533
2005	0.156	0.398	0.440
2006	0.208	0.350	0.452
2007	0.134	0.315	0.364

Notes: The table reports results from fixed-effect regressions of total factor productivity (TFP) on a dummy variable containing four quantiles based on product quality distribution within each six-digit industry and year. In these regressions, we control for six-digit industry fixed effects. Quality is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets.

D First-stage regression results

Table D1: Impact of Chinese competition on the skill premium, first-stage results (Table 2)

Regression in column	(2)	(4)		(6)	
Dependent variable	China share	China share	China share*TFP	China share	China share*Export status
IV for China share	0.38***	0.367***	0.654***	0.353***	-0.007**
	(0.026)	(0.023)	(0.132)	(0.028)	(0.003)
IV for China share*TFP		0.023***	0.489***		
		(0.004)	(0.039)		
IV for China share*Export status				0.131***	0.545***
				(0.051)	(0.046)
F statistics	216.45	122.65	81.69	118.45	101.15
Plant FE	X	X	X	X	X
Region-Year FE	X	X	X	X	X
Sector-Year FE	X	X	X	X	X
Observations	39753	39753	39753	39753	39753

Notes: The table reports results of the first-stage regressions of the IV regressions in columns (2), (4), and (6) in table 2. The instrument for the China share variable is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. ** and *** indicate coefficients significantly different from zero at the 5% and 1% level, respectively.

Table D2: First-stage regression results of IV regressions in table 4

Regression in column	(2)	(4)	
Dependent variable	China share	China share	China share*Foreign
IV for China share	0.314***	0.299***	-0.025***
	(0.032)	(0.032)	(0.004)
IV for China share*Foreign		0.506***	0.979***
		(0.075)	(0.072)
F statistics	96.83	82.31	124.94
Product-Plant-Market FE	X	X	X
Region-Year FE	X	X	X
Sector-Year FE	X	X	X
Observations	102423	102423	102423

Notes: The table reports results of the first-stage regressions of the IV regressions in columns (2) and (4) in table 4. The instrument for the China share variable is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles and observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the plant level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

E Impact on skill intensity, number, and wage of each type of workers

Table E1: Impact on skill intensity

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	0.107	0.240	0.091	0.145	0.105	0.200
	(0.091)	(0.241)	(0.091)	(0.300)	(0.111)	(0.283)
L.China share*Initial TFP			0.013	0.039		
			(0.015)	(0.043)		
L.China share*Initial Export status					0.009	0.140
					(0.179)	(0.394)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.449		116.253		154.645
KP Wald F stat		216.449		60.889		97.384

Notes: The dependent variable is the log of the skill intensity. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses.

Table E2: Impact on number of white-collar workers

	Baseline		TFP		Export Status	
	(1) FE	(2) IV	(3) FE	(4) IV	(5) FE	(6) IV
L.China share	-0.045	0.092	-0.044	-0.049	-0.006	0.173
	(0.103)	(0.241)	(0.101)	(0.301)	(0.119)	(0.280)
L.China Share*Initial TFP			-0.000	0.057		
			(0.015)	(0.043)		
L.China Share*Initial Export status					-0.122	-0.283
					(0.214)	(0.433)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.449		116.253		154.645
KP Wald F stat		216.449		60.889		97.384

Notes: The dependent variable is the log of the number of white-collar workers. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses.

Table E3: Impact on number of blue-collar workers

	Baseline		TFP		Export Status	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV	FE	IV	FE	IV
L.China share	-0.152*	-0.148	-0.135	-0.194	-0.110	-0.027
	(0.088)	(0.239)	(0.089)	(0.293)	(0.099)	(0.257)
L.China Share*Initial TFP			-0.013	0.019		
			(0.014)	(0.043)		
L.China Share*Initial Export status					-0.130	-0.424
					(0.184)	(0.448)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.449		116.253		154.645
KP Wald F stat		216.449		60.889		97.384

Notes: The dependent variable is the log of the number of blue-collar workers. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses.

Table E4: Impact on wage of blue-collar workers

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	-0.095*	-0.078	-0.104**	-0.087	-0.109*	0.034
	(0.048)	(0.139)	(0.051)	(0.161)	(0.060)	(0.162)
L.China share*Initial TFP			0.007	0.004		
			(0.008)	(0.023)		
L.China share*Initial Export status					0.046	-0.393**
					(0.088)	(0.199)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.449		116.253		154.645
KP Wald F stat		216.449		60.889		97.384

Notes: The dependent variable is the log of the wages of blue-collar workers. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table E5: Impact on wage of white-collar workers

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	-0.186***	-0.398**	-0.199***	-0.575***	-0.205**	-0.435**
	(0.070)	(0.182)	(0.073)	(0.222)	(0.080)	(0.212)
L.China share*Initial TFP			0.010	0.072**		
			(0.013)	(0.033)		
L.China share*Initial Export status					0.059	0.133
					(0.142)	(0.288)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.449		116.253		154.645
KP Wald F stat		216.449		60.889		97.384

Notes: The dependent variable is the log of the wages of white-collar workers. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10%, 5%, and 1% level, respectively.

F Robustness check tables

F.1 Impact on skill premium, robustness checks

Table F1: Impact on skill premium - Control for TFP

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	-0.092	-0.319*	-0.095	-0.487**	-0.096	-0.469**
	(0.072)	(0.179)	(0.073)	(0.207)	(0.084)	(0.214)
L.China share*Initial TFP			0.003	0.068**		
			(0.011)	(0.032)		
L.China share*Initial Export status					0.012	0.525*
					(0.150)	(0.284)
L.TFP	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.409		116.267		154.600
KP Wald F stat		216.563		60.890		97.347

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table F2: Impact on skill premium - Control for interactions between exchange rate and export/import shares

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	-0.093	-0.319*	-0.097	-0.485**	-0.094	-0.479**
	(0.072)	(0.179)	(0.073)	(0.206)	(0.084)	(0.216)
L.China Share*Initial TFP			0.003	0.068**		
			(0.011)	(0.032)		
L.China share*Initial Export status					0.003	0.547*
					(0.153)	(0.297)
L.Exchange rate*Initial Export share	0.003	0.004	0.003	0.003	0.003	-0.003
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
L.Exchange rate*Initial Import share (M)	0.000	0.000	0.000	0.001	0.000	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
L.Exchange rate*Initial Import share (I)	0.002	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		159.900		116.363		151.084
KP Wald F stat		217.849		60.904		93.622

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table F3: Impact on skill premium - Control for US tariff

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	-0.114	-0.293	-0.116	-0.476**	-0.121	-0.445**
	(0.071)	(0.180)	(0.072)	(0.208)	(0.084)	(0.215)
L.China Share*Initial TFP			0.002	0.075**		
			(0.011)	(0.032)		
L.China share*Initial Export status					0.023	0.535*
					(0.146)	(0.287)
L.US tariff	0.305*	0.296	0.307*	0.339*	0.306*	0.311*
	(0.185)	(0.185)	(0.186)	(0.187)	(0.185)	(0.184)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	38561	38561	38561	38561	38561	38561
KP LM stat		158.291		115.374		155.895
KP Wald F stat		215.625		61.170		99.111

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table F4: Impact on skill premium - Control for output tariff

	Baseline		TFP		Export Status	
	FE	IV	FE	IV	FE	IV
	(1)	(2)	(3)	(4)	(5)	(6)
L.China share	-0.090	-0.321*	-0.095	-0.497**	-0.095	-0.474**
	(0.073)	(0.180)	(0.073)	(0.208)	(0.084)	(0.215)
L.China share*Initial TFP			0.003	0.078**		
			(0.011)	(0.033)		
L.China share*Initial Export status					0.027	0.551*
					(0.147)	(0.292)
L.Output tariff	0.199	0.199	0.201	0.254*	0.199	0.200
	(0.128)	(0.128)	(0.128)	(0.131)	(0.128)	(0.128)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	38285	38285	38285	38285	38285	38285
KP LM stat		157.434		115.372		152.863
KP Wald F stat		214.96		60.49		96.777

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table F5: Impact on skill premium - Control for input tariff

	Baseline		TFP		Export Status	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV	FE	IV	FE	IV
L.China share	-0.083	-0.266	-0.085	-0.430**	-0.095	-0.448**
	(0.072)	(0.179)	(0.073)	(0.211)	(0.084)	(0.215)
L.China Share*Initial TFP			0.001	0.060*		
			(0.011)	(0.033)		
L.China share*Initial Export status					0.038	0.636**
					(0.150)	(0.277)
L.Input tariff	0.136	0.062	0.138	0.131	0.132	0.001
	(0.527)	(0.527)	(0.528)	(0.532)	(0.528)	(0.530)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39352	39352	39352	39352	39352	39352
KP LM stat		150.818		111.990		145.221
KP Wald F stat		201.973		51.256		89.981

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table F6: Impact on skill premium - Separate China shares

	(1)	(2)	(3)	(4)	(5)	(6)
	FE	IV	FE	IV	FE	IV
L.China share (dom)	-0.100	-0.333*	-0.099	-0.517**	-0.093	-0.466**
	(0.069)	(0.185)	(0.069)	(0.217)	(0.084)	(0.214)
L.China share (exp)	0.049	0.100	0.081	0.109	0.053	0.024
	(0.074)	(0.116)	(0.077)	(0.126)	(0.073)	(0.134)
L.China Share(dom)*Initial TFP			0.006	0.071**		
			(0.010)	(0.033)		
L.China Share(exp)*Initial TFP			-0.023	-0.009		
			(0.014)	(0.022)		
L.China Share (dom)*Initial Export status					-0.023	0.517
					(0.141)	(0.330)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	39753	39753	39753	39753	39753	39753
KP LM stat		141.052		111.211		58.050
KP Wald F stat		102.729		29.420		45.195

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. * and ** indicate coefficients significantly different from zero at the 10% and 5% level, respectively.

Table F7: Impact on skill premium - Subsample of inital non-exporters

	Baseline		TFP	
	(1)	(2)	(3)	(4)
	FE	IV	FE	IV
L.China share	-0.086	-0.528**	-0.089	-0.659***
	(0.085)	(0.234)	(0.086)	(0.249)
L.China Share*Initial TFP			0.003	0.067*
			(0.013)	(0.038)
Plant FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	29666	29666	29666	29666
KP LM stat		115.903		89.844
KP Wald F stat		139.416		42.642

Notes: The regressions are estimated for the subsample of non-exporting firms in the first year available. The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), (6), and (8) is the share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela). The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10%, 5%, and 1% level, respectively.

Table F8: Impact on skill premium - Subsample of initial exporters

	Baseline		TFP	
	(1)	(2)	(3)	(4)
	FE	IV	FE	IV
L.China share	-0.103	0.088	-0.101	-0.036
	(0.136)	(0.263)	(0.128)	(0.442)
L.China Share*Initial TFP			-0.001	0.036
			(0.019)	(0.069)
Plant FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	10087	10087	10087	10087
KP LM stat		43.733		26.412
KP Wald F stat		100.391		29.323

Notes: The regressions are estimated for the subsample of exporting firms in the first year available. The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), (6), and (8) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with skill premiums that are below the 1st and above the 99th percentiles. Standard errors clustered at the plant level are shown in parentheses.

Table F9: Impact on skill premium - Full sample

	FE (1)	IV (2)	FE (3)	IV (4)	FE (5)	IV (6)
L.China share	-0.073	-0.338	-0.083	-0.570**	-0.091	-0.577**
	(0.079)	(0.212)	(0.078)	(0.247)	(0.088)	(0.255)
L.China share*Initial TFP			0.008	0.095**		
			(0.011)	(0.039)		
L.China share*Initial Export status					0.058	0.841***
					(0.170)	(0.316)
Plant FE	X	X	X	X	X	X
Region-Year FE	X	X	X	X	X	X
Sector-Year FE	X	X	X	X	X	X
Observations	40877	40877	40877	40877	40877	40877
KP LM stat		161.136		119.800		154.622
KP Wald F stat		207.444		58.319		91.814

Notes: The dependent variable is the log of the skill premium. The instrument used in the IV regressions in columns (2), (4), and (6) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. Standard errors clustered at the plant level are shown in parentheses. *** and ** indicate coefficients significantly different from zero at the 1% and 5% level, respectively.

F.2 Impact on product quality, robustness checks

Table F10: Impact on log(price)

	Baseline		Market	
	(1)	(2)	(3)	(4)
	FE	IV	FE	IV
L.China share	-0.183***	-0.354**	-0.175***	-0.351**
	(0.053)	(0.155)	(0.060)	(0.156)
L.China share*Foreign			-0.042	-0.189
			(0.093)	(0.198)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	102467	102423	102467	102423
KP LM stat		104.275		110.912
KP Wald F stat		96.828		54.412

Notes: The dependent variable is the log of unit value. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. ** and *** indicate coefficients significantly different from zero at the 5% and 1% level, respectively.

Table F11: Impact on product quality - Control for TFP

	Baseline		Market	
	(1)	(2)	(3)	(4)
	FE	IV	FE	IV
L.China share	-1.353***	-5.146***	-1.697***	-5.201***
	(0.420)	(1.362)	(0.483)	(1.365)
L.China share*Foreign			1.795***	4.569***
			(0.555)	(1.106)
L.TFP	0.050*	0.050*	0.050*	0.051*
	(0.027)	(0.027)	(0.027)	(0.027)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	102467	102423	102467	102423
KP LM stat		104.279		110.917
KP Wald F stat		96.824		54.409

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F12: Impact on product quality - Control for marginal cost

	Baseline		Market	
	(1)	(2)	(3)	(4)
	FE	IV	FE	IV
L.China share	-1.391***	-5.058***	-1.740***	-5.108***
	(0.438)	(1.373)	(0.507)	(1.375)
L.China share*Foreign			1.767***	4.459***
			(0.572)	(1.113)
L.Log(product-plant MC)	-0.060***	-0.059***	-0.060***	-0.059***
	(0.017)	(0.017)	(0.017)	(0.017)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	99773	99729	99773	99729
KP LM stat		101.793		108.785
KP Wald F stat		95.676		54.660

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F13: Impact on product quality - Control for interactions between exchange rate and export/import shares

	Baseline		Market	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
L.China share	-1.458***	-4.861***	-1.631***	-4.969***
	(0.416)	(1.417)	(0.503)	(1.465)
L.China share*Foreign			0.931	2.663*
			(0.656)	(1.593)
L.Exchange rate*Initial Export share	-0.095***	-0.103***	-0.089***	-0.085***
	(0.025)	(0.024)	(0.027)	(0.031)
L.Exchange rate*Initial Import share (M)	-0.137***	-0.142***	-0.137***	-0.141***
	(0.035)	(0.036)	(0.035)	(0.035)
L.Exchange rate*Initial Import share (I)	-0.026**	-0.025**	-0.026**	-0.026**
	(0.012)	(0.012)	(0.012)	(0.012)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	102467	102423	102467	102423
KP LM stat		107.179		111.171
KP Wald F stat		99.517		53.910

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F14: Impact on product quality - Control for US tariff

	Baseline		Market	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
L.China share	-1.358***	-4.702***	-1.683***	-4.736***
	(0.415)	(1.252)	(0.469)	(1.251)
L.China share*Foreign			1.718***	4.232***
			(0.545)	(1.034)
L.US tariff	1.964	2.087	1.973	2.083
	(1.607)	(1.611)	(1.606)	(1.611)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	98378	98343	98378	98343
KP LM stat		106.319		113.694
KP Wald F stat		97.912		55.610

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F15: Impact on product quality - Control for output tariff

	Baseline		Market	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
L.China share	-1.343***	-4.871***	-1.739***	-4.918***
	(0.428)	(1.299)	(0.498)	(1.300)
L.China share*Foreign			2.054***	4.509***
			(0.571)	(1.087)
L.Output tariff	5.374***	5.386***	5.415***	5.468***
	(2.023)	(2.038)	(2.027)	(2.045)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	101027	100983	101027	100983
KP LM stat		103.376		110.333
KP Wald F stat		96.510		54.778

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F16: Impact on product quality - Control for input tariff

	Baseline		Market	
	(1)	(2)	(3)	(4)
	FE	IV	FE	IV
L.China share	-1.316***	-5.033***	-1.655***	-5.147***
	(0.425)	(1.442)	(0.490)	(1.457)
L.China share*Foreign			1.764***	4.626***
			(0.565)	(1.170)
L.Input tariff	2.607	0.935	2.108	-0.013
	(5.471)	(6.046)	(5.557)	(6.213)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	101466	101422	101466	101422
KP LM stat		100.666		105.552
KP Wald F stat		92.336		50.409

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with skill premiums that are above the 1st and below the 99th percentiles. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F17: Impact on product quality - Trim sample based on sales

	Baseline		Market	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
L.China share	-1.154**	-6.089***	-1.730***	-6.179***
	(0.547)	(1.784)	(0.636)	(1.784)
L.China share*Foreign			2.985***	6.730***
			(0.679)	(1.329)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	93037	92993	93037	92993
KP LM stat		82.063		87.144
KP Wald F stat		71.980		39.753

Notes: The dependent variable is the log of the product quality, which is estimated using a sample of observations with sales that are above the 5th and below the 95th percentiles within each sector in both domestic and foreign markets. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

Table F18: Impact on product quality - Full sample

	Baseline		Market	
	FE	IV	FE	IV
	(1)	(2)	(3)	(4)
L.China share	-1.342***	-5.051***	-1.664***	-5.108***
	(0.416)	(1.382)	(0.478)	(1.385)
L.China share*Foreign			1.672***	4.367***
			(0.542)	(1.114)
Product-Plant-Market FE	X	X	X	X
Region-Year FE	X	X	X	X
Sector-Year FE	X	X	X	X
Observations	104402	104358	104402	104358
KP LM stat		102.393		108.941
KP Wald F stat		87.787		49.107

Notes: The dependent variable is the log of the product quality. *Foreign* is an indicator taking a value of 1 if a product is sold in the foreign market and 0 otherwise. The instrument used in the IV regressions in columns (2) and (4) is the share of Chinese imports in high-income countries in 1994 (Australia, Austria, Denmark, Finland, France, Germany, Greenland, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, and United Kingdom) for export sales and share of Chinese imports in South American countries (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Paraguay, Peru, Uruguay, and Venezuela) for domestic sales. The Kleibergen-Paap LM statistic for underidentification and the Kleibergen-Paap Wald F statistic for weak identification of the instrumental variable are reported at the bottom of the table. The table trims observations with estimated quality that are below the 5th and above the 95th percentiles within each sector and in both domestic and export markets. Standard errors clustered at the product level are shown in parentheses. *** indicates coefficients significantly different from zero at the 1% level.

G Derivation of preferences

The representative consumer's utility maximisation can be written as

$$\max_{q_i^c} U \qquad subject\ to \qquad q_0^c + \int_{i\in\Omega} p_i q_i^c di = I^c, \tag{G1}$$

where $U = q_0^c + \alpha \int_{i\in\Omega} q_i^c di + \beta \int_{i\in\Omega} z_i q_i^c di - \frac{1}{2}\gamma \int_{i\in\Omega} (q_i^c)^2 di - \frac{1}{2}\eta (\int_{i\in\Omega} q_i^c di)^2$ and I^c is the consumer's total income. First order condition of utility maximisation problem is

$$p_i = \alpha - \gamma q_i^c + \beta z_i - \eta Q^c, \tag{G2}$$

where $Q^c = \int_{i\in\Omega} q_i^c di$. Thus,

$$q_i^c = \frac{1}{\gamma}(\alpha - p_i + \beta z_i - \eta Q^c), \tag{G3}$$

where

$$Q^c = \frac{1}{\gamma}(\alpha N - \int_{i\in\Omega} p_i di + \beta \int_{i\in\Omega} z_i di - \eta N Q^c), \tag{G4}$$

and N is a measure of consumed varieties. Let $\bar{p} = \frac{1}{N}\int_{i\in\Omega} p_i di$ and $\bar{z} = \frac{1}{N}\int_{i\in\Omega} z_i di$, with some simple algebra, we can get

$$Q^c = \frac{\alpha N}{\eta N + \gamma} - \frac{N\bar{p}}{\eta N + \gamma} + \frac{N\beta\bar{z}}{\eta N + \gamma}. \tag{G5}$$

H Tariff Data

Tariff data for Mexico and the US under NAFTA are taken from the Trade Analysis Information System (TRAINS) Database maintained by the United Nations Conference on Trade and Development (UNCTAD), which is obtained from the World Integrated Trade Solution (WITS) of the World Bank. Since TRAINS does not have US tariff data under NAFTA in 1998, we use the US tariff data under NAFTA from the Integrated Database (IDB) of the World Trade Organization for the year 1998, which is also obtained from WITS. Tariffs are available at the eight-digit Harmonized System (HS8) level.

We drop all the observations which experienced an increase in tariff values over years at the HS8 level. Subsequently, we compute the average tariff of the eight-digit HS codes within six-digit (HS6) categories and merge the tariff data with the eight-digit product classification in the manufacturing plant-level data using the manually constructed concordance. When multiple HS6 codes correspond to a single product code, we use the average tariff across corresponding HS6 codes.

Tariff data for Mexico before 1995 is only available for the year 1991. However, tariff schedules in Mexico remain constant from 1991 to 1993 (Faber, 2014). Therefore, we use the tariff data for Mexico in 1991 as its data for the year 1993. Tariff data for Mexico under NAFTA are not available for 1994, 1996, 1997, 1998, 2000, 2001, and 2003, and tariffs for the US are not available for 1994. To construct the tariff schedules for these years, we follow Kikkawa, Mei, and Santamarina (2019) to use the institutional details of NAFTA, i.e. under NAFTA Mexican tariffs on imports from the US and US tariffs on imports from Mexico were reduced annually at a constant rate. For example, if a tariff was 20 percent in 1993 and 10 percent in 1995, it is assumed to be 15 percent in 1994. If a tariff was 0 percent in 1995, it is assumed to be 0 percent in 1994.

To construct a measure that captures the impact of access to cheaper imported inputs as a result of tariff reductions under NAFTA, we compute intermediate input tariffs using the 2003 Input-Output (IO) table obtained from the Instituto Nacional de Estadística y Geografía

(National Institute of Statistics and Geography, henceforth INEGI) website. The 2003 IO matrix is not ideal because it is taken towards the end of our sample period, but this is the most recent available Mexican IO table since 1980. This table has been used widely in the literature (Faber, 2014; Kikkawa et al., 2019).

Since the Input-Output table is available at the three-digit NAICS classification (the North American Industry Classification System), we first use the NAICS-ISIC (the International Standard Industrial Classification) concordance provided by INEGI and the ISIC-HS concordance to compute the average output tariff (i.e. Mexican tariffs imposed on imports from the US) at the three-digit NAICS. The input tariffs are computed by weighting the output tariffs by their input cost shares, as follows:

$$input\ tariff_{kt} = \sum_j w_{jk} * output\ tariff_{jt}$$

where w_{jk} is class k's share of intermediate inputs coming from class j in 2003, and $output\ tariff_{jt}$ is the average output tariff applied by Mexico on goods from the US in class j. The input tariffs, then, are matched with the 1994 Clasificación Mexicana de Actividades y Productos (Mexican System of Classification for Activities and Products, henceforth CMAP) in the plant-level data using the NAICS-CMAP concordance provided by INEGI. When multiple NAICS-3 codes correspond to a single CMAP-6 code, we use the average tariff across corresponding NAICS-3 codes.