

THE IMPACT OF CHINESE COMPETITION ALONG THE QUALITY LADDER

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December 2017

Abstract

We document that French firms with low prices are significantly more affected by the rise of China in international markets. To rationalize this finding, we propose a random coefficient, discrete choice model of demand in which consumers have heterogeneous preferences regarding product characteristics and prices. This heterogeneity in preferences implies more realistic substitution patterns across producers relative to existing trade models. In particular, it allows for French varieties located at the bottom of the price distribution to be closer substitutes to Chinese goods, due to their proximity in the product space. Moreover, it implies that low-quality French firms are willing to upgrade their product quality to escape low-cost countries competition. Using firm-level trade data, we estimate the model and quantify the unequal effect of China across French exporters in the footwear industry, between 1997 and 2010. We find substantial differences across firms: the rise in Chinese exports implied losses in market shares five times larger at the bottom of the price distribution relative to the top. Moreover, we show that allowing French firms to adjust their product quality does little to help them escape Chinese competition.

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1 Introduction

One of the most salient change in the global economy over the last twenty years has been the surge of Chinese products in export markets. From 1991 to 2010, the share of Chinese exports in total manufacturing exports went from 2 percent to 15 percent. A burgeoning literature has documented the adverse effects of this global change for developed countries: while consumers benefit from lower prices and higher variety, regions hosting industries in competition with Chinese producers have suffered important economic and socioeconomic damages, relative to other regions.

If the impact and consequences of the ‘China shock’ on different industries have been extensively studied, little has been said on the heterogeneous effects of Chinese competition within industries. One of the reason for this silence is that most international trade models assume that all firms, within a defined industry, are equally affected by a rise in foreign competition.¹ However, the international trade literature also highlights the existence of a large within-industry dispersion in productivity, input usage and product quality. Therefore, this rising Chinese competition is likely to generate differentiated effects within industries, with potential aggregate consequences on inequality or allocative efficiency.

In this paper, we develop and estimate a model of demand in international markets, in which firms operating in the same industry can be differently affected by foreign competition. Following the industrial organization literature, we introduce heterogeneity in consumer preferences to generate substitution patterns across varieties that depend on their proximity in the product space. Therefore, our model can predict why firms that produce low-quality goods are more affected by the rise in Chinese exports than firms producing high-end products. Estimating the model using international trade data from French shoe producers, we document substantial differences in the effect of Chinese competition depending on the position of a firm in the price distribution. Moreover, we show that firms’ ability to upgrade their products does little to avoid the profit losses due to the rise of Chinese exports.

We start by showing reduced form evidence of the heterogeneous impact of Chinese exports across firms. Using firm-level data from France and industry-level data from China, we show that markets with the highest Chinese penetration rates display larger differences between French and Chinese prices. This is consistent with the weight of low price firms in French exports decreasing as Chinese exports grow. Similarly, we find that French firms with low prices have recorded a larger decrease in market shares, relative to high-price firms, in markets which have seen an increase in Chinese market shares. When focusing on the footwear industry, we also observe that among French firms, the relative market share of low-price firms decreases over time, as the market share of China rises.

Based on this evidence, we develop an empirical model in which consumers have heterogeneous preferences. In particular, following Berry, Levinsohn, and Pakes (1995), we introduce a random coefficient logit demand model in which consumers have different price-elasticities and heterogeneous preferences for French goods. A direct implication of this heterogeneity in consumers’ preferences is to make Chinese varieties more substitutable to cheap French varieties.

¹This is true for models with Constant Elasticity of Substitution (CES) demand. The use of nested CES demand or discrete choice models can reduce these stark patterns of substitution but only in very limited ways.

Intuitively, Chinese varieties and French low-cost varieties both serve the same price-sensitive consumers. Therefore, when Chinese firms enter a market, price-sensitive consumers switch to purchasing Chinese goods, which happens mostly at the expense of low-cost varieties. In addition to this demand model, we allow firms to endogenously adjust the quality of their product. Producing higher quality goods comes at a higher marginal cost. Therefore, firms trade-off between serving a cheap product (price competitiveness) and serving an appealing product (non-price competitiveness).

In order to estimate the model, we combine French firm-level trade data and country-level trade data from 40 countries for the footwear industry between 1997 and 2010. We focus on the footwear industry that resembles in many aspects the manufacturing sectors that suffered from the rise of Chinese exports. An advantage of using international trade data to estimate this demand system is the availability of instruments to address the endogeneity of prices. We use exchange rates on exports to instrument country-level prices while firm-level prices are instrumented using the average exchange rate on imports, weighted by the importing shares of different source countries. Moreover, the use of international trade data helps the identification of the random coefficients that mostly relies on the joint variation across destinations in the income distribution and in the cross-elasticity between low and high-cost varieties.

The estimation of the model confirms the existence of heterogeneous consumers. We find that the heterogeneity in price-elasticity is particularly related to the income of the consumer: richer consumers display lower price-elasticity and higher preference for French goods relative to other countries. As a consequence, we find significant differences in the mark-ups charged by French firms, ranging from 15 to 35 percent. We also find large differences across firms in their cross-elasticity to China. While it is almost zero for many firms, some firms' cross-elasticity goes beyond 2. These firms with large cross-elasticities sell cheap products and thus compete for the same consumers as Chinese varieties. As a consequence, their sales are highly sensitive to Chinese prices.

The estimation results also allow us to shed light on the quality decisions of French firms. We first document that the quality of French exporters have converged during the sample period: firms with low quality in 1997 record a larger growth of their quality over time, which is consistent with quality upgrading as a response to the increasing Chinese competition. Moreover, we take advantage of this strategic response to Chinese competition to estimate an important parameter of our model: the elasticity of marginal costs to quality. We construct an instrument that captures quality changes related to changes in foreign competition, and therefore exogenous to changes in firms' costs. This instrument allows us to overcome the endogeneity issue between firms' productivity and quality choice, and to document the positive and convex impact of quality on firms' marginal costs. Measuring this relationship between quality and marginal costs is essential to quantify the quality response of French firms to a change in the competitive environment.

Finally, we use the estimated model to perform counterfactual experiments. In particular, we measure what would have been the market shares of individual French exporters of shoes, had Chinese exports maintained their characteristics from before 2001. The result of this experiment confirms the heterogeneous impact along the quality ladder. We find that the impact on market shares is more than three times larger at the bottom of the price distribution relative the top:

the first decile in the price distribution records a median nine percent gain in market share while the tenth decile only sees a three percent gain. Moreover, we find that the ability of firms to upgrade the quality of their product did little to help them mitigate the effect of Chinese competition. When quantifying the impact of the rise of China, we find that allowing firms to upgrade quality reduces the impact of Chinese competition by 5 percent for the lowest price decile. Interestingly, this mitigating effect of quality upgrading by low-quality firms, implies stronger losses for high-quality firms because of a ripple effect along the quality ladder.

This paper relates to a fast-growing literature on the effect of trade with China and with low-cost countries. A important part of this literature has emphasized the adverse effects in developed economies on industries or regions exposed to Chinese import competition. In particular, Autor, Dorn, and Hanson (2013), Autor, Dorn, Hanson, and Song (2014) and Pierce and Schott (2016) document negative labor market effects in the United States. Malgouyres (2016) and Dauth, Findeisen, and Suedekum (2017) find similar negative effects of import competition respectively in France and Germany. Several papers showed that these adverse effects spillover on public goods (Feler and Senses, 2017) and political outcomes (Dorn et al., 2016; Che et al., 2016). Moreover, Khandelwal (2010) shows that US industries with shorter quality ladder are more likely to suffer from a rise in low-cost country competition. By contrast, we emphasize that the effect of China may vary substantially across firms within a given industry.

Similarly to our question, some studies have pointed out that low-cost country competition may have distributional effects within sectors, including Bernard, Jensen, and Schott (2006), Martin and Mejean (2014) and Bloom, Draca, and Van Reenen (2016). Ahn, Han, and Huang (2017) shows that Korean firms increase their innovation effort in response to Chinese competition, even more so in industries with higher prices relative to Chinese firms. Our paper differs in that we rely on a structural approach. This approach allows us to back out unobservable variables such as profits, mark-ups or quality which are key to fully understand and quantify the mechanisms at play. Moreover, we are able to quantify how much quality upgrading helped French producers mitigating the consequences of the China shock. Verhoogen (2008) and Bastos, Silva, and Verhoogen (Forthcoming) show how changes in market access trigger adjustments in product quality at the firm level. More related to our paper is Holmes et al. (2014) who also emphasizes the heterogeneous effect of China in a structural framework. In their theory however, the heterogeneity is not explained in terms of low- and high-cost firms, but in terms of firms producing standardized versus specialized goods.

Our paper also relates to a growing literature in international trade that introduces non-homotheticity in consumers' preferences. Fajgelbaum, Grossman, and Helpman (2011) and Fajgelbaum and Khandelwal (2016) study the consequences of heterogeneous preferences on the gains from trade. Faber and Fally (2017) and Hottman and Monarch (2017) introduce non-homothetic preferences to analyze the heterogeneous impacts across consumers of changes in product prices. Closer to our paper, Adao, Costinot, and Donaldson (2017) and Heins (2016) introduce mixed preferences to generates heterogeneous patterns of substitution across countries. In contrast to these papers, we utilize these preferences to obtain more realistic substitution patterns at the micro level, in order to quantify the heterogeneous effects of low-cost competition across firms.

The rest of the paper is organized as follows. Section 2 presents the data and some motivating evidence that Chinese competition varies along the quality ladder. Section 3 introduces our empirical model and section 4 details the estimation of the parameters. Section 5 describes the results of the estimation. In section 6, we implement some counterfactual experiments on the impact of China. Section 7 concludes.

2 Data and Motivating Evidence

In this section, we describe the main data sources and we present reduced form evidence of the differential impact of Chinese competition along the quality ladder.

2.1 The Data

In our paper, we combine two sources of information on international trade. The first source of trade data is BACI database, developed by CEPII. This comprehensive database uses original procedures to harmonize the United Nations COMTRADE data (Gaulier and Zignago, 2010). BACI data is broken down by exporting country, importing country, year and 6-digit product code of the Harmonized System (HS) classification. The HS classification evolves over time. We apply the algorithm described in Pierce and Schott (2012) in order to obtain well-defined and time-invariant product categories. We refer to this new classification as “HS6+”.

Second, we exploit firm-level trade data collected by French customs administration. These data provide a comprehensive record of the yearly values and quantities exported and imported by French firms from 1997 to 2010. Trade flows are disaggregated at the firm, country and eight-digit product category of the combined nomenclature (CN).² In order to make both data sources homogeneous, we aggregate customs data at the HS6+ level. This is straightforward since the NC classification is nested inside the HS classification.

As is common in the trade literature, we use unit values - the ratio between the value and the weight of a trade flow - as a proxy for prices. For some product categories, exporting firms are free to declare the volume of the shipment in terms of a supplementary unit (USUP), which is product specific (for instance, the USUP for shoes is the number of pairs), rather than in tons. In order to harmonize the customs data, we compute a conversion rate from USUP to tons based on flows for which both tonnage and USUP are declared. We use this conversion rate to input a tonnage to observations where only the USUP is declared.

Since we want to use these trade data to estimate a demand system, we need to construct prices which are as close as possible to those faced by final consumers. To this end, we convert unit values to the importer’s currency. We also inflate unit values by an ad valorem transportation cost computed from the National Supply and Use Tables, which are part of the World Input-Output Database (WIOD). These data contain the free-on-board (FOB) value and the transportation costs for international trade between 38 countries at the 2-digit level of the Sta-

²Only annual values which exceeds a legal threshold are included in the dataset. For instance, in 2002, this threshold was 100,000 euros. This cutoff is unlikely to significantly affect our study since, this same year, the total values of flows contained in the dataset represented roughly 98 percent of the aggregated estimates of French international trade.

tistical classification of products by activity (CPA) from 1995 to 2011.³ We compute the ad valorem transportation cost at the importing country, exporting-country, CPA level by taking the average over the period of the ratio between transportation costs and FOB trade.

2.2 Stylized Facts

In this section, we provide reduced-form evidence of the impact of Chinese competition along the quality ladder. In particular, we compare the relative dynamics of high and low-price French firms in export markets that recorded a large increase in Chinese penetration.

In order to do so, we start by adopting a “difference-in-differences” approach, by categorizing French exporters based on their position in the price distribution, and export markets, based on their changes in Chinese penetration rates. First, to identify high and low-price French exporters, we regress log prices between 1997 and 2000 on a set of firm fixed effects and a set of destination-product-year fixed effects: $\ln price_{fdpt} = FE_f + FE_{dpt} + u_{fdpt}$. Then, we label an exporter ‘low-price’ if it belongs to the first quartile of the FE_f distribution and ‘high-price’ if it belongs to the fourth quartile. Second, we classify export markets depending on their changes in Chinese market shares during our time period. In order to classify markets, we compute the change in Chinese market share at the HS6+ product level between two periods: 1997-2000 and 2006-2010. Product markets at the bottom and the top quartile of this change are respectively labeled as ‘control’ and ‘treated’ markets.

Based on these categories, we can now investigate the relative dynamics of French exporters, in markets with different changes in Chinese market shares. To study these dynamics, we compute the log-change in market shares of French exporters from 1997 and compare these average log-changes between high and low-price firms in control and treated markets.⁴ Figure 1 reports these average percentage changes for each group-year.

From figure 1, we see that high-price firms did not suffer from the rise in Chinese competition: the average log-change in market shares have been relatively similar between treated and control firms. By contrast, among low-price firms, varieties exporting to markets that were hit by the China shock lost substantially more market shares than untreated ones. This suggests that the rise in Chinese competition has been mostly harmful to cheap French varieties.

To confirm the statistical significance of these patterns, we relate the exports of French firms to the penetration rates of Chinese competition. Namely, we regress the logarithm of exports of a given firm in a destination market on the market share of Chinese producers. In order to investigate heterogeneous effects across French firms, we interact the Chinese market shares with the price quartile of the firm (as defined above). Formally, we estimate the following regression

$$\ln export_{fdpt} = \sum_{q=1}^4 \alpha_q \{PQ_{fdp} = q\} + \sum_{q=1}^4 \delta_q \{PQ_{fdp} = q\} \times CHN_{dpt} + FE + \varepsilon_{fdpt},$$

with CHN_{dpt} the market share of China on market dp at date t , PQ_{fdp} the price quartile

³The data actually covers 40 countries but we drop Luxembourg, which is merged with Belgium in the trade data, as well as France, since we do not observe the domestic sales and prices of French firms.

⁴Computing the log-change in market shares relative to the initial year is convenient to compute averages across markets. In the appendix, figures 14 and 15 show that this pattern is robust when using the change in market shares, or when classifying markets based on low-cost countries competition rather than Chinese competition.

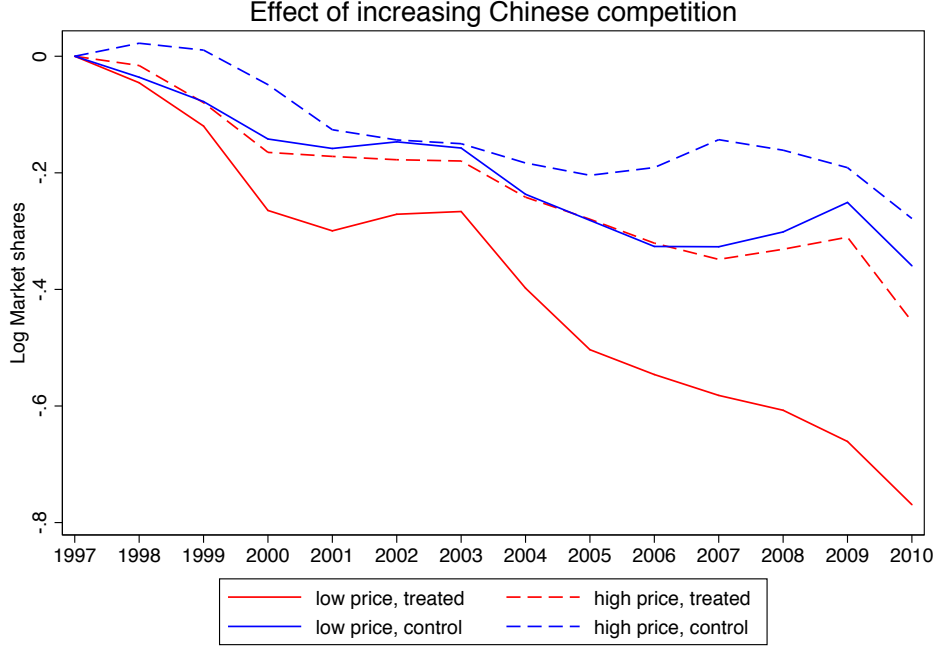


FIGURE 1: The China Shock Impacts Low-Price Varieties More

Notes: This figure shows the change in the log market share since 1997, $\ln s_{fdpt} - \ln s_{fdp97}$, averaged at the group-year level, for four different groups of export flows: control-low price; control-high price; treated-low price; treated-high price.

variety fdp belongs to and FE a set of fixed effects. Specifically, we use two sets of fixed effects: in a first specification, we use destination-HS6-year fixed effects to control for market-specific conditions, and in a second we add a second fixed effect at the firm-HS6-destination level. The inclusion of this second fixed effect gives us our preferred specification since it measures heterogeneous change in log-exports of French firms related to changes in Chinese competition. Our coefficients of interest are $\{\delta_q, q = 1, \dots, 4\}$. We expect the δ 's to be increasing with q , suggesting that the China shock is less detrimental to high-price varieties. The results are reported in table 1.

In column (1), we only include a market-year fixed effect FE_{dpt} , such that the identification comes from relative export values between exporters in the same destination market. The coefficients related to the interaction terms are all positive and monotonically increasing, which implies that high price firms have relatively larger export values in market with large Chinese penetration. In column (2), our preferred specification, we include a firm-product-destination fixed effect which leads to a within-firm identification of the parameters. Once again, interaction coefficients are significantly larger than zero, which means that when the market shares of Chinese firms increase, high-price firms do relatively better than low-price firms. Even if the magnitude of the coefficients is much more limited, and the coefficients on quartiles 2 to 4 do not differ statistically, the conclusion remains similar: firms from the first price quartile lose more from the China shock.

In column (3) and (4), we verify that these results extend at the extensive margin. We proceed by estimating a linear probability model where the dependent variable $Survival_{fdpt}$ is

TABLE 1: High-price Varieties suffer less from Chinese Penetration

Dependent variable:	<i>log export</i>		<i>Survival</i>	
	(1)	(2)	(3)	(4)
2nd price quartile	−0.179*** (0.009)		0.011*** (0.001)	
3rd price quartile	−0.223*** (0.009)		0.021*** (0.001)	
4th price quartile	−0.077*** (0.009)		0.012*** (0.001)	
Low-cost penetration				
× 2nd price quartile	0.453*** (0.049)	0.086*** (0.032)	0.009* (0.005)	0.030*** (0.006)
× 3rd price quartile	0.608*** (0.048)	0.098*** (0.032)	0.011** (0.005)	0.045*** (0.006)
× 4th price quartile	0.885*** (0.047)	0.064** (0.030)	0.036*** (0.004)	0.071*** (0.005)
N	5,179,864	5,167,637	5,179,864	5,167,637
Year × Prod × Dest FE	Y	Y	Y	Y
Firm × Prod × Dest FE	N	Y	N	Y

Notes: Standard errors clustered at the firm-destination-product level between parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

a dummy equal to one if trade flow f_{pd} is still active in $t + 1$. Just like column (1) and (2), columns (3) and (4) only differ because column (4) includes a producer fixed effect. Results on survival confirm that the differential effect of China also applies at the extensive margin: according to column (4), the effect of a one percentage point increase in Chinese market share on the probability to remain active the next period is 7 percentage points larger at the top of the price distribution than at the bottom.

A potential explanation of these results could be that low-price firms are less resilient to all types of competition, including Chinese competition. To show that this pattern is specific to competition from low-cost producers, we run the same regression but looking at the effect of competition from high-cost countries. Results displayed in table 2 show that the effect of high-cost competition is symmetric: when the market share of high-cost producers is increasing, high-price firms tend to suffer slightly more relative to low-price firms. This result is in line with a demand system that generates stronger substitution patterns between firms that are closer in the product space.

What makes low-price varieties more sensitive to the China shock? Our hypothesis is that this stronger substitution come from the fact that they lie closer to Chinese varieties in the price distribution. Figure 2 documents this pattern by plotting the different distribution of Chinese and French prices in export markets with varying levels of Chinese penetration. To build this figure, we first divided all year-destination-hs6+ markets into quartiles, according to their Chinese market share. Then, for each quartile, we plot the distribution of Chinese and

TABLE 2: Low-price Varieties suffer less from high-cost competition

Dependent variable:	<i>log export</i>		<i>Survival</i>	
	(1)	(2)	(3)	(4)
2nd price quartile	0.028*		0.023***	
	(0.016)		(0.001)	
3rd price quartile	0.025*		0.035***	
	(0.015)		(0.001)	
4th price quartile	0.24		0.029***	
	(0.015)		(0.001)	
High-cost penetration				
× 2nd price quartile	−0.43	−0.078*	−0.011***	−0.021***
	(0.034)	(0.040)	(0.002)	(0.007)
× 3rd price quartile	−0.52	0.013	−0.012***	−0.034***
	(0.033)	(0.034)	(0.002)	(0.007)
× 4th price quartile	−0.64**	−0.059	−0.033***	−0.049***
	(0.032)	(0.038)	(0.004)	(0.007)
N	5,391,250	5,376,741	5,179,864	5,167,637
Year × Prod × Dest FE	Y	Y	Y	Y
Firm × Prod × Dest FE	N	Y	N	Y

Notes: Standard errors clustered at the firm-destination-product level between parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

French prices, expressed in log-difference to the mean price on the market. Figure 2 reports unweighted histograms (left panels) and histograms weighted by market shares (right panels). The upper panels correspond to price distributions on markets with less Chinese penetration.

The first take-away from figure 2 is that, within narrowly defined markets, Chinese prices are lower than French prices. This implies that cheap French exporters charge prices more comparable to those of Chinese exporters and are therefore potentially more substitutable to Chinese varieties. The demand system presented in next section is consistent with this idea.

The second take-away from figure 2 is that the French and Chinese distributions overlap less on markets with higher Chinese penetration. This may just be a simple corollary of the evidence we presented above that low-price varieties give in more market shares to China: this mechanically triggers a composition effect which shifts up French price distribution. However, one can also rationalize the difference between the different panels of figure 2 with a within-firm vertical differentiation story whereby French exporters upgrade the quality of their products to shelter from Chinese penetration. In section 5, we present the results of our structural estimation and we show that French firms have upgraded the quality of their products over the period, the more so the lower their price, consistently with the escape competition story. In the supply side of our model, we endogenize firms' product quality in order to quantify the amount of quality upgrading due to the China shock.

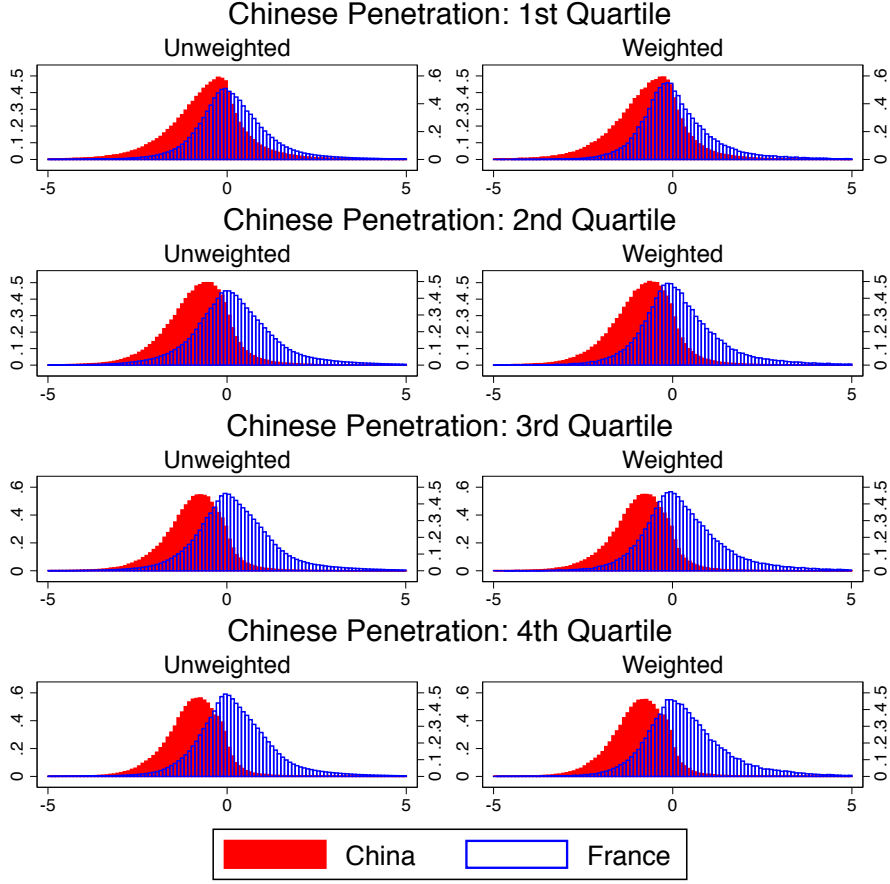


FIGURE 2: Chinese Competition and the Distribution of French and Chinese Prices

Notes: This figure shows the distribution of Chinese and French prices, expressed in log-difference to the mean price on the destination-product-year market. We split destination markets into four quartiles, based on the level of Chinese penetration, and we plot both distributions separately for each quartile. On the right panels, the distribution is obtained weighting each individual flow by their share on the destination-product-year market. On the left panels, individual flows are unweighted.

3 Model

3.1 Demand Side

The global economy is a collection of destinations d , populated with a continuum of consumers. Each consumer i picks one variety j and consumes $q_{ijt} = \frac{e(y_i)}{p_{jt}}$ physical units of it, with $e(y)$ the budget allocated by a consumer with log-income y to the consumption of shoes. A variety is produced by a unique firm. A firm can produce multiple varieties, which differ in their product characteristics. For instance, Lacoste leather shoes and Lacoste fabric shoes are two different varieties.

The utility derived by consumer i from consuming variety j is

$$u_{ijt} = q_{ijt} \exp \left(\frac{x_{jt}\beta_i + \overbrace{\gamma_f + \xi_{jdt}}^{\text{Quality } \lambda_{jdt}} + \varepsilon_{ijt}}{\exp(\alpha_i)} \right).$$

x_{jt} is a K -dimensional (row) vector of observable product characteristics, γ_f is a utility shifter that is specific to firm f , which produces variety j . ξ_{jdt} captures deviations in consumers' valuation of the goods supplied by firm f across varieties and destinations. We define $\lambda_{jdt} \equiv \gamma_f + \xi_{jdt}$, as the quality of a variety j on destination d . λ_{jdt} contains any unobservable characteristic that raises the valuation of j from the point of view of all consumers in destination d . ε_{ijt} is an idiosyncratic shock in consumer i 's valuation of variety j . Finally, $\frac{1}{\exp(\alpha_i)}$ is the quality elasticity of utility for consumer i . We do not constrain the sign of the relationship between α_i and y_i . However, we expect this relationship to be negative as richer consumers value quality more.

In each destination, consumers choose among the set of foreign varieties available, that we denote Ω_d . In addition to this set of foreign varieties, the consumer can also decide to opt for the outside good. In the empirical application, this outside good is the domestic variety of the good. The indirect utility associated to any foreign variety j is

$$V_{ijt} = x_{jt}\beta_i - \exp(\alpha_i) \ln p_{jt} + \gamma_f + \xi_{jdt} + \varepsilon_{ijt}$$

while the valuation of the outside good is defined as $V_{i0t} = -\exp(\alpha_i) \ln p_{0t} + \gamma_0 + \xi_{0t} + \varepsilon_{i0t}$.

Consumers pick the variety that maximizes their indirect utility. Since indirect utilities are only defined up to a constant, we normalize the utility shifter of the outside good - $\gamma_0 + \xi_{0t}$ - to zero. Therefore, the measured quality of foreign varieties should be interpreted in deviation to the quality of the outside good. Note, however, that we do not set the price of the outside good to zero: such normalization would impose unnecessary constraints on the substitution patterns between the outside good and other varieties. In the estimation, we therefore account for the price of the domestic good.

Individual and aggregate demand We assume that the idiosyncratic shock ε_{ijt} is distributed according to a Type I extreme-value distribution. Therefore, the probability that consumer i in destination d buys variety j is

$$\begin{aligned} \mathbb{P}_{ijdt} &= \frac{\exp \left(x_{jt}\beta_i - \exp(\alpha_i)(\ln p_{jdt} - \ln p_{0dt}) + \gamma_f + \xi_{jdt} \right)}{1 + \sum_{j \in \Omega_d} \exp \left(x_{jt}\beta_i - \exp(\alpha_i)(\ln p_{jdt} - \ln p_{0dt}) + \gamma_f + \xi_{jdt} \right)} \\ &= \frac{\exp(\delta_{jdt} + \mu_{ijdt})}{1 + \sum_{j \in \Omega_d} \exp(\delta_{jdt} + \mu_{ijdt})} \end{aligned}$$

with $\delta_{jdt} \equiv x_{jt}\beta + \gamma_f + \xi_{jdt}$ and $\mu_{ijdt} \equiv x_{jt}(\beta_i - \beta) - \exp(\alpha_i)(\ln p_{jdt} - \ln p_{0dt})$. This notation allows us to separate the components of the indirect utility that are common across consumers (δ_{jdt}), and the ones that are idiosyncratic (μ_{ijdt}). In order to discipline the variation in consumer

preferences, we assume that

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi y_i + \Sigma \nu_i, \quad y_i \sim F_{y,d}(y), \nu_i \sim F_\nu(\nu) \quad (1)$$

where Π is a $K + 1$ row-vector of parameters, Σ is a $(K + 1) \times m$ matrix of parameters and ν_i is a m column-vector of random variables.

Equation (1) says that the random coefficients depends linearly on the log-income of the consumer y_i and a vector of random shocks ν_i . Importantly, the distribution of y_i , $F_{y,d}$, depends on the demographic characteristics of each destination market d .⁵

Each consumer i is fully characterized by their log income y_i and the shock on their preferences, ν_i . As a consequence, we can redefine the probability of a consumer with log-income y and preference shock ν to consume a variety j as

$$\mathbb{P}_{jdt}(y, \nu) = \frac{\exp(\delta_{jdt} + \mu_{jdt}(y, \nu))}{1 + \sum_{j \in \Omega_d} \exp(\delta_{jdt} + \mu_{jdt}(y, \nu))}.$$

Knowing this probability, it follows that the sales of variety j in destination d is

$$r_{jdt} = \int e(y(\nu)) \frac{\exp(\delta_{jdt} + \mu_{jdt}(y, \nu))}{1 + \sum_{j \in \Omega_d} \exp(\delta_{jdt} + \mu_{jdt}(y, \nu))} F_{y,d}(y) F_\nu(\nu) dy d\nu$$

Therefore, the market shares of producer j (in sales) in destination d is

$$\begin{aligned} s_{jdt} &\equiv \frac{r_{jdt}}{\sum_{j \in \Omega_d} r_{jdt}} = \frac{\int e(y) \mathbb{P}_{jdt}(y, \nu) F_{y,d}(y) F_\nu(\nu) dy d\nu}{\sum_{j \in \Omega_d} \int e(y) \mathbb{P}_{jdt}(y, \nu) F_{y,d}(y) F_\nu(\nu) dy d\nu} \\ &= \int \mathbb{P}_{jdt}(y, \nu) \omega_d^{(1)}(y, \nu) dy d\nu \end{aligned} \quad (2)$$

with $\omega_d^{(1)}(y, \nu) \equiv \frac{e(y) F_{y,d}(y) F_\nu(\nu)}{\int e(y) F_{y,d}(y) F_\nu(\nu) dy d\nu}$. The revenue market shares of variety j is the probability that a consumer picks the variety, averaged across consumers, and weighted by the budget of each consumer.

Optimal mark-up From the demand function faced by varieties, we can derive their optimal price. Assuming constant marginal costs of production, the profit of a variety j is $\pi_{jdt} = r_{jdt}(1 - \frac{c_{jdt}}{p_{jdt}})$. Using the first order condition on firm's profit leads to the following optimal pricing rule:

$$p_{jdt} = \left(1 + \frac{1}{\int (1 - \mathbb{P}_{jdt}(y, \nu)) \exp(\alpha(y, \nu)) \omega_{jdt}^{(2)}(y, \nu) dy d\nu} \right) c_{jdt}, \quad (3)$$

with $\omega_{jdt}^{(2)}(y, \nu) \equiv \frac{e(y) \mathbb{P}_{jdt}(y, \nu) F_{y,d}(y) F_\nu(\nu) dy d\nu}{\int e(y) \mathbb{P}_{jdt}(y, \nu) F_{y,d}(y) F_\nu(\nu) dy d\nu}$ the share of consumers with characteristics y and ν in the sales of the firm.

Intuitively, the mark-up charged by a firm is a function of the average individual price elasticity, weighted by the sales made to each consumer. Therefore, firms producing goods that

⁵In the next section, we provide more details regarding the distribution of ν_i and y_i .

are more appealing to rich consumers set higher mark-ups, since their average consumer is less price-sensitive. One can see that in the absence of heterogeneity across consumers, we obtain the usual pricing rule: $p_{jdt} = \left(1 + \frac{1}{(1-\mathbb{P}_{jdt})\exp(\alpha)}\right) c_{jdt}$. In this framework, mark-ups decrease with the price elasticity of the representative consumer and increase with the market share of the firm.

3.2 Supply Side

Technology In order to be able to assess the way French firms adjust their quality to the China shock, we need to take a stand on the way quality λ impacts firms' production costs. We assume that quality only enters marginal costs. More specifically, we consider the following relationship between the log-marginal costs and quality:

$$\ln c_{jdt}(\lambda) = h(\lambda) + x_{jdt}\rho + \eta_{jdt}\lambda + \varphi_{jdt}, \quad (4)$$

with η_{jdt} a measure of the capability of variety j to supply high quality and φ_{jdt} an inverse measure of physical productivity. The presence of η_{jdt} explains that product quality varies across firms. $h(\lambda)$ is a flexible function of λ . Although we do not impose restrictions on $h(\cdot)$, we find in the estimation that it is increasing and convex, which guarantees the existence of an interior solution on quality. We describe this solution in the following paragraph.

Optimal Quality When choosing their optimal quality, firms trade-off between producing a more appealing product, and selling a more affordable product. Equation (5) is the first order condition on quality λ that describes this trade-off. On the left-hand side of the equation, marginally increasing quality has a positive effect on profit since the product is now more appealing to consumers, which boosts sales. At the same time, serving better quality raises the marginal cost of production, which translates into higher prices and therefore lower sales. This effect is on the right-hand side of the first-order condition and depends on the cost-elasticity of quality and a weighted average price-elasticity of the firm consumers.

$$\int (1 - \mathbb{P}_{jdt}(y, \nu)) \omega_{jdt}^{(2)}(y, \nu) dy d\nu = \frac{\partial \ln c}{\partial \lambda} \int \exp(\alpha(y, \nu)) (1 - \mathbb{P}_{jdt}) \omega_{jdt}^{(2)}(y, \nu) dy d\nu \quad (5)$$

When Chinese competition kicks in, firms from advanced economies mostly lose market shares over price-elastic consumers. This means that the sales-weighted average price elasticity faced by firms is now smaller in absolute terms. As a consequence, firms have a stronger incentive to upgrade their products since they now serve consumers which won't be so much bothered by the higher price of higher quality goods.

It is crucial to note that this mechanism would not be at play in the absence of price elasticity heterogeneity across consumers. In that special case, Chinese competition would not change the composition of firms' sale across consumer and would thus leaves untouched firms' optimal quality. In next section, we present our strategy to estimate the model, and in particular the distribution of price elasticity across consumers.

4 Empirical Implementation

In this section, we describe how we bring the model to the data. We start by describing the preparation of the data and the choice of the Footwear industry to perform the estimation. Then, we discuss the specification we estimate and the methods we use to deal with the endogeneity problem of the demand system, and the presence of zeros in trade data. Finally, we describe the algorithm and method to estimate the model and recover demand and supply-side parameters.

4.1 Data preparation

The footwear industry We estimate the model using data from the footwear industry. Specifically, we focus on eight hs6 positions within the hs2 position number 64: ‘Footwear; Gaiters and the like; parts of such articles’. These eight positions exclude sport shoes, waterproof shoes and shoe parts.⁶

We pick the footwear industry mainly for two reasons. First, shoes are a well-defined consumer good. This allows us to obtain prices that are consistent across varieties, and product characteristics that can be inferred from the data. we are able to include four product characteristics in the estimation: whether the sole of the shoe is in leather (*Leather sole*), whether the top of the shoe is in leather (*Leather top*), whether the top is in fabric (*Fabric top*), and whether the shoe covers the ankle (*Boot*). Appendix 7 provides details regarding this procedure.

The second reason for the relevance of the footwear industry is that it mimics the recent trends in manufacturing. The Chinese market share in the footwear industry has increased significantly over the period, moving from 20% in the average destination market in 1997 to 35% in 2010. In light of these features, we expect the footwear industry to exhibit an heterogeneous response to China along the quality ladders, similarly to other French industries. Figure 3 provide evidence of these patterns. As the market share of Chinese producers rose, the market share of cheap French shoes dropped. In the meantime, expensive French shoes were able to maintain, and even slightly gain market shares.⁷

A more comprehensive picture can be seen from movements in the distribution of prices. In figure 4, we report for each year from 1997 to 2010, the distribution of Chinese and French prices, weighted by their market shares. This figure shows that, as the market share of Chinese producers increase, the price distribution of French shoes has been diverging upward from Chinese prices. This movement suggests that French producers have upgraded the quality of their shoes, or that market shares have been reallocated from low-price to high-price producers.

To summarize, the footwear industry is appealing mostly because the China shock is large and the patterns of response to the shock are qualitatively comparable to those of the average French industry.

Data cleaning In order to ensure the robustness of our findings, we clean the data to avoid the presence of outliers that may drive our results. In particular, we perform two operations. First, we eliminate markets with a small number of producers. Specifically, we drop observations when

⁶The list of these eight positions is reported in appendix 7.

⁷In the appendix, figure 16 describes the evolution in logarithm of market shares using the same definition from the previous section.

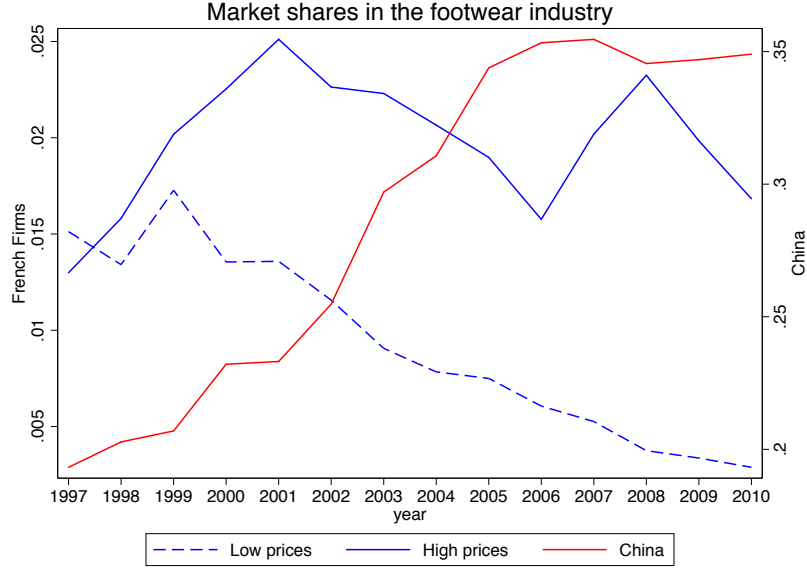


FIGURE 3: The China Shock Hits Cheap Shoes Harder

Notes: The figure shows the average market share for Chinese exporters and two different groups of French exporters. High-price and low-price observations respectively belong to the fourth and first quartiles of the distribution of average prices before 2001.

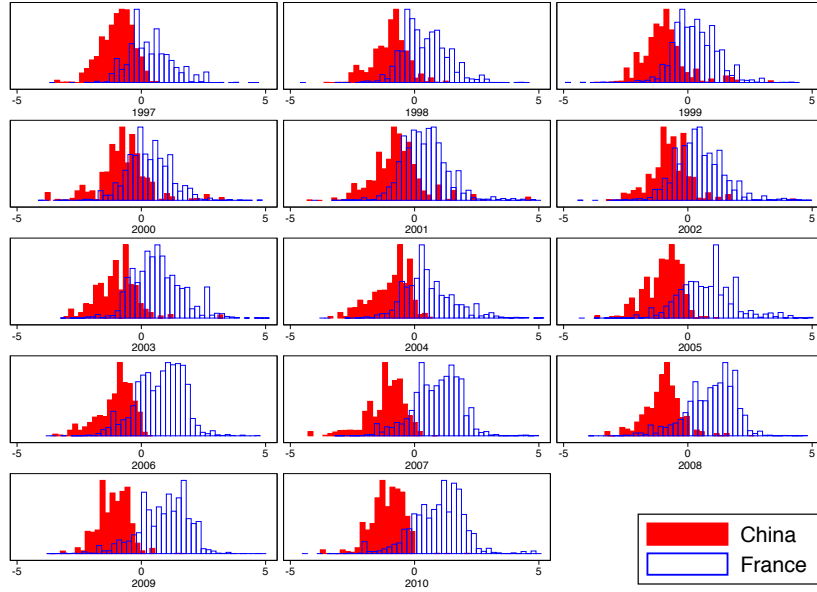


FIGURE 4: The Price of French and Chinese Shoes Diverge as China Grows

Notes: This figure shows the distribution of Chinese and French prices, expressed in log-difference to the mean price in the destination-product-year market, weighted by their share in the destination-product-year market.

the number of firms within a year-destination-hs6 bin is less than 5. Second, we eliminate outliers in the dataset. In particular, we eliminate observations when the logarithm of price is lower than -2 or larger than 2 from the average price in their market. Similarly, we drop observations when the logarithm of price is lower than -1 or larger than 1 from the average price of their producer. This procedure aims at ensuring that the measurement issues that exist in trade data does not

impact our estimation.

This cleaning procedure leaves us with 175 766 observations during the sample period, out of which 99 533 are French. In table 3, we report summary statistics for the 4104 French firms that are part of the sample. We notice that the median firm has only three observations, which is peculiar of trade data. Moreover, we see a large dispersion in the price of one kilogram of shoes, ranging from 10 US\$ at the 5th percentile to 291 US\$ at the 95th percentile.

TABLE 3: Summary statistics for French firms

	<i>Mean</i>	<i>p5</i>	<i>p25</i>	<i>p50</i>	<i>p75</i>	<i>p95</i>
By firm:						
# observations	24.2	1	1	3	13	103
# destinations	3.8	1	1	1	4	16
# products	24.2	1	1	2	4	7
Price	83.1	10.7	25.0	47.4	96.2	291

Notes: Prices CIF in US dollars. Sample of 4104 firms.

Outside good In order to implement the estimation, we also need information regarding the outside good in each market. In our context, the domestic variety is the most natural outside good available.⁸ Therefore, we construct its market share by computing the share of domestic consumption in total consumption from the WIOD database. Even though we can obtain this information for every year and destination country, this information is only available for broad product classifications. As a consequence, we compute the market share of the outside good as the domestic market share for the category ‘Leather, Leather and Footwear’. Moreover, the estimation requires to know the price of the outside good. For this purpose, we proxy the price of the domestic good in a country from the price of its exports as measured in the BACI dataset. More specifically, we use the average FOB unit value of the country exports.

4.2 Model specification

After having described the sample used to perform the estimation, we provide details on the specification of the model. We start by describing the structure of the random coefficients in the model, then describe how we deal with endogenous selection and price endogeneity.

Random coefficients As emphasized in the previous section, a crucial aspect of the framework is to allow for heterogeneity in consumer preferences. This heterogeneity is introduced through heterogeneous coefficients in the utility function. Even though it is possible to introduce heterogeneous coefficients for all product characteristics, we decide to restrict this heterogeneity to the price coefficient α_i and the preference for French goods β_i^F . Specifically, we introduce three

⁸See Khandelwal (2010) for a similar assumption in the same context.

different shocks to account for heterogeneity between consumers: a first shock captures variations in price-elasticity that are related to the income of the consumer. A second shock captures variations in price-elasticity that are driven by unobservables. Finally, a third shock measures the variation in preferences for French goods. This last shock introduces a nested structure in the demand for shoes: in the presence of this shock, all things equal, a French variety is a closer substitute to another French variety than to a non-French variety.

Formally, equation (1) from the previous section becomes

$$\begin{pmatrix} \alpha_i \\ \beta_i^F \end{pmatrix} = \begin{pmatrix} \alpha \\ 0 \end{pmatrix} + \begin{pmatrix} \Pi_\alpha \\ 0 \end{pmatrix} y_i + \begin{pmatrix} \Sigma_\alpha & \Sigma_{\alpha,F} \\ 0 & \Sigma_F \end{pmatrix} \nu_i$$

with β_i^F the preference for French goods. $\nu_i \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}; \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}\right)$ and $y_i \sim N(\mu_{y_d}, \sigma_{y_d})$, where μ_{y_d} and σ_{y_d} are respectively the mean and standard deviations of the logarithm of the income distribution in destination d.

To summarize the specification, the demand system is parameterized by 5 non-linear parameters, that enter the distribution of coefficients α and β^F . We call this set of non-linear parameters θ . In addition to these parameters, there are 5 parameters that enter linearly in the estimation of the demand system. 4 of these parameters captures the valuation of each product characteristic described in the previous paragraph and the fifth parameter measures the selection on unobservables described in the next paragraph.

Endogenous selection An important complication with the use of international trade data comes from the large extend to which countries and firms self-select into destination markets. A significant number of countries and firms do not export to some destinations due to the large fixed and variable costs linked with the exporting activity. This endogenous selection leads to the existence of many 'zeros' in trade data that potentially bias the estimation of structural parameters. A natural way to model this endogenous selection is to consider the existence of a threshold in the mean utility of the producer $\delta_{jdt} = x_{jdt}\beta + \lambda_f + \xi_{jdt} > \bar{\delta}_{dt}$ under which producers decide to not export to a destination.

To account for this endogenous selection, we perform a 'Heckman'-type correction by running, in a first stage, a selection equation. Specifically, we estimate a probit model of export participation using the same set of instruments used in the main estimation, a set of destination-year fixed effects. Moreover, to account for firm-specific fixed effects, we follow the method by Mundlak (1978) by adding the firm-specific average of the observed exogenous characteristics. Assuming that the structural error of the model, ξ , follows a normal distribution, we can construct the inverse Mills ratio and use it as additional variable in the structural model. Under this distributional assumption, the inclusion of the Mills ratio as additional regressor allows us to test for endogenous selection, but also to control for the bias in the structural error of observed trade flows. Importantly, we estimate two separate models of export participation for French firms and foreign countries: aggregate and firm-level data are likely to have different thresholds that explain export participation; running separate probit models takes into account those differences.

Instruments The estimation procedure previously described requires instrumental variables that are orthogonal to the structural error of the model. The choice of these instruments is an old and still ongoing debate in the literature on demand estimation. These variables need to be correlated with the prices charged by firms (and potentially the product characteristics if one does not assume the exogeneity of these characteristics) but uncorrelated with the structural error of the model which captures the residual demand for a variety. Most papers in the literature have used either the so-called “BLP instruments”, which use the product characteristics of competitors as exogenous shifter of the mark-up charged by firms, or the “Hausman instruments” which take advantages of prices set in other markets to provide exogenous shifts in prices due to correlation in costs across markets.

Without fully describing the potential issues with the instruments used in the literature, we believe the use of international trade data provides an arguably better set of instruments through the existence of exchange rates between countries. These exchange rates, moving with macroeconomic conditions, directly affect the final price charged by a firm in foreign markets. Moreover, because these exchange rates fluctuate based on macroeconomic conditions, they are unlikely to be correlated with demand shocks or quality decisions made by shoes producers, which constitutes the structural error of the model. Therefore, we follow the approach used in the international trade literature aiming at estimating demand with trade data and use exchange rates as instruments for prices.⁹

The use of exchange rates between origin and destination countries as instruments is not sufficient to estimate the model, though. Since we use trade flows from individual French firms, the identification of the substitution between French firms also requires instrumental variables that vary between firms. To overcome this issue, we construct firm-specific cost shifters by taking advantage of the spatial structure of French firms’ imports. We construct an import-weighted exchange rate that measures movements in exchange rates faced by French firms on their import. Because these firms import from different sets of countries, they are exposed to different variations in exchange rates. This instrument has shown to have a significant impact on firms’ export prices and therefore constitutes a valid instruments for French firms.¹⁰ Formally, this instrument is defined as

$$\overline{RE\overline{R}}_{ft} = \sum_{o \in \mathcal{S}_f} \omega_{fo} \log \left(\frac{CPI_{ot}}{CPI_{ft}} e_{oFt} \right)$$

where \mathcal{S}_f is the set of source countries of firm f , ω_{fo} is the import share from origin o for firm f , CPI_{ct} is the consumer price index of country c at time t and e_{oFt} the exchange rate from origin o to France at time t . Importantly, the import share ω does not vary across time such that all time-variations in this instrument comes from movements in real exchange rates. To maintain this weight constant, we either use the import shares the year a firm starts exporting (preferred specification), or the average import shares over the sample period.

From a similar idea, we derive three other instruments using the lagged value of the real exchange rates instead of the contemporaneous value, and by interacting this instrument with

⁹See Khandelwal (2010) or Hallak and Schott (2011) for instance.

¹⁰See Piveteau and Smagghue (2017) for a further discussion on these instruments

the ratio of total import expenditures and total export revenue, in order to capture the prevalence of imports flows in the total costs of the firm. Therefore, we obtain four instruments that exploit movements in exchange rates as exogenous shifters in the production costs of firms. These movements generates prices adjustments by firms while being unrelated with demand shocks or endogenous quality decisions made by the firms.

4.3 Estimation algorithm

The model is estimated using a Generalized Method of Moments (GMM) estimator. GMM algorithms rely on orthogonality conditions between an error term $\varepsilon(\theta)$, function of the model parameters, and a set of instruments $Z = [z_1, \dots, z_L]$ such that

$$E[z_l \varepsilon(\theta_0)] = 0, \quad \text{for } l = 1, \dots, L \quad (6)$$

where θ_0 is the true value of the parameter. Following BLP, we use the structural error of the model to construct the error term in these orthogonality conditions. From the model derived in the previous section, the structural error of the model ξ_{jdt} is defined as a utility shifter that explain the relative market shares of each product. From equation (2), the market share of a product is

$$s_{jdt} = \int \frac{\exp(\delta_{jdt} + \mu_{jt}(y, \nu))}{1 + \sum_{j \in \Omega_d} \exp(\delta_{jdt} + \mu_{jt}(y, \nu))} \omega^{(1)}(y, \nu) dy d\nu$$

such that the predicted market shares depend on the vector of mean utility level δ , the vector of observables x and $\ln p$, and the non-linear parameters θ .

This formulation provides a mapping between the mean utility level δ_{jdt} of a variety and the corresponding market share. Therefore, conditional on the set of parameters θ , and the observables, we can solve for the unknown δ such that the predicted market shares $s(\delta, x, \ln p; \theta)$ equals the observed market shares S_{jdt} . For this purpose, we use the contraction mapping suggested by BLP: from a given set of δ^h , we compute $s(\delta^h, x, \ln p; \theta)$ and set

$$\delta^{h+1} = \delta^h + \log S - \log s(\delta^h, x, \ln p; \theta). \quad (7)$$

We perform the contraction until the minimum of the squared difference between the updated and previous δ is below a given threshold. Formally, we iterate until

$$\min \left\{ (\delta_{jdt}^{h+1} - \delta_{jdt}^h)^2 \right\}_{j,d,t} < 10^{-12}.$$

A complication in the iterative process arises from the computation of the object $s(\delta^h, x, \ln p; \theta)$. This object requires the integration of the shocks y and ν distributed according to $F_{y,d}$ and F_ν . To perform this integration, we rely on the Gaussian assumption to numerically approximate this integral using Gauss-Hermite quadrature.¹¹

¹¹In particular, we use nodes and weights on sparse grids provided by Heiss and Winschel (2008) with an accuracy level of 5. The total number of points evaluated in the integral is 96. The convergence of the contraction mapping is also accelerated by using the Squarem acceleration method developed in Varadhan and Roland (2004), and programmed in Matlab by Chris Conlon.

We denote the resulting $\delta \equiv \delta(S, x, \ln p; \theta)$ since they depend on observables, and the non-linear parameters θ . We then regress $\delta(S, x, \ln p; \theta)$ on product characteristics x , firm dummies γ and the inverse of the mills ratio m . This gives us an estimate of the remaining five parameters that appears in the utility function. Finally, we obtain the structural errors of the model from

$$\hat{\xi} = \delta(S, x, \ln p; \theta) - \hat{\beta}x - \hat{\gamma} \quad (8)$$

We can then use these structural errors $\hat{\xi}$ to obtain $\hat{\varepsilon} \equiv \hat{\xi} - \hat{\beta}_m m$ and create the orthogonality conditions that identify the parameters θ . Moreover, this last step highlights the advantage of using the structural error to create our GMM conditions rather than the market shares predicted by the model. In this setup, the only parameters that enter the GMM problem are the ones related to the distribution of the random coefficient. By contrast, the parameters that enter the mean utility level can be directly obtained by simple linear regression, hence reducing the dimensionality of the search algorithm.

In situations where the number of instruments is larger than the number of parameters ($\dim(\theta) < L$), it is not possible to find parameters θ that set the sample analogs of all the moments in equations (6) equal to zero. In this case, we use a weight matrix Φ and define the GMM estimate as the parameters that minimize the weighted distance of these moments to zero. Therefore, the GMM estimate is defined as

$$\hat{\theta} = \operatorname{argmin}_{\theta} \varepsilon(\theta)' Z \Phi Z' \varepsilon(\theta)$$

We minimize the GMM objective function using a standard optimizer to which we provide the gradient of the problem. This minimization does not appear problematic and the results look robust to different starting conditions.¹² We use $\Phi = (Z'Z)^{-1}$ in a first step and then construct an estimate of the optimal weighting matrix by setting $\Phi = (Z'\varepsilon(\hat{\theta})\varepsilon(\hat{\theta})'Z)^{-1}$ in a second step.

4.4 Recovering supply-side parameters

From the estimation of the demand system, we are able to estimate the mark-up of firms and infer their marginal costs. Having in hand these costs, we can estimate how they vary with product characteristics, and more importantly with the product quality offered by each firm. Our definition of product quality follows the literature: we measure the utility shifter of each variety in each market after controlling for product characteristics and prices.¹³

Estimating the correlation between costs and quality poses an identification challenge. Since product quality is an endogenous choice of the firm, it is very likely to be related to the productivity of the firm: more productive firms might be willing to invest in product quality if we believe there exists complementarity between firms performance and quality choices.¹⁴ On the contrary, firms with higher productivity and lower prices might face relatively price sensitive consumers, which would reduce their incentives to invest in product quality. Therefore, identifying

¹²We use `fminunc` from Matlab with the trust-region algorithm.

¹³In our context, we look at quality changes within a specific product. Therefore, we do not capture quality changes that might occur when firms change product characteristics.

¹⁴see Kugler and Verhoogen (2012) for a model with complementarity between firms performance and quality choice, and empirical evidence of such a relationship.

the causal effect of product quality on costs is an empirical challenge.

Fortunately, our model provides us with instruments to tackle this endogeneity issue. Precisely, due to the existence of heterogeneous consumers, the average price-elasticity faced by firms depends on the location of the firms on the quality ladder, but also the market shares of foreign firms that compete with French firms. For instance, consider two firms operating in the same market, one at a low price and a second at a high price. If the penetration of Chinese firms increases in this market, the firm with a low price will see her average consumer becoming less price sensitive, because her more price-sensitive consumers will reallocate their consumption towards Chinese products. As a consequence, it is now profitable for this firm to upgrade its product, while the incentives of the high-price firm are left unchanged.

To construct this instrument, we use the first-order condition of the quality choice made by each firm. Re-arranging optimality condition (5), we show that the optimal quality is such that the quality- elasticity of costs is equal to the inverse of a weighted average price-elasticity:

$$\frac{1}{\frac{\partial \ln c}{\partial \lambda}} = \int \exp(\alpha(y, \nu)) \omega_{jdt}^{(3)}(y, \nu) dy d\nu$$

$$\text{with } \omega_{jdt}^{(3)}(y, \nu) = \frac{\mathbb{P}_{jdt}(y, \nu)(1 - \mathbb{P}_{jdt}(y, \nu))e(y, \nu)F_{y,d}(y)F_{\nu}(\nu)}{\int \mathbb{P}_{jdt}(y, \nu)(1 - \mathbb{P}_{jdt}(y, \nu))e(y, \nu)F_{y,d}(y)F_{\nu}(\nu)dyd\nu}$$

Therefore, our instrument is defined as

$$instr_{jdt} = \int \exp(\alpha(y, \nu)) \tilde{\omega}_{jdt}(y, \nu) dy d\nu$$

$$\text{with } \tilde{\omega}_{jdt}(y, \nu) = \frac{\tilde{\mathbb{P}}_{jdt}(y, \nu)(1 - \tilde{\mathbb{P}}_{jdt}(y, \nu))e(y, \nu)F_{y,d}(y)F_{\nu}(\nu)}{\int \tilde{\mathbb{P}}_{jdt}(y, \nu)(1 - \tilde{\mathbb{P}}_{jdt}(y, \nu))e(y, \nu)F_{y,d}(y)F_{\nu}(\nu)dyd\nu}$$

$$\tilde{\mathbb{P}}_{jdt} = \frac{\exp(\delta_{jd0} + \mu_{jd0}(y, \nu))}{1 + \exp(\delta_{jd0} + \mu_{jd0}(y, \nu)) + \sum_{j' \neq j} \exp(\delta_{j'dt} + \mu_{j'dt}(y, \nu))}$$

This formula exactly captures the intuition provided in the paragraph above by measuring the sales-weighted average price elasticity faced by each firm. When the instrument increases, a firm has less incentive to invest in quality. Moreover, in order to obtain an exogenous change in this price elasticity, we keep the quality and price of the firm at their initial value. Therefore, the time variation of this instrument is only due to changes in the competitive environment faced by each firm. We believe this instrument allows us to obtain a causal effect of quality on costs by generating exogenous changes in the incentives for firms to produce quality.

5 Results

We first describe the two steps of the estimation: the estimation of the export participation equation to construct the inverse Mills ratio and the parameters estimates obtained through GMM estimation. We then discuss several outcomes of the model to describe how the demand system captures heterogeneity across firms. Finally, we describe the relationship between marginal costs and quality that will allow us to quantify the quality response of French firms to a change in Chinese competition.

5.1 Estimation results

The first step of the estimation aims to construct the inverse Mills ratio that accounts for endogenous selection. We extend the dataset to include all zeros that reflect the absence of trade flows between a producer and a destination. We then estimate a probit model using the instruments as regressors. Results of this estimation are displayed in table 4.

TABLE 4: Selection equation

Export participation		
	Countries	Firms
RER_{odt}	-0.054^{***} (0.01)	-0.17^{***} (0.01)
\overline{RER}_{ft}		0.028 (0.07)
\overline{RER}_{ft-1}		-0.94^{***} (0.07)
$\overline{RER}_{ft} \times \frac{\text{imp}_f}{\text{exp}_f}$		-0.020 (0.03)
$\overline{RER}_{ft-1} \times \frac{\text{imp}_f}{\text{exp}_f}$		0.10^{***} (0.03)
N	157 472	5 529 608

Notes: All specifications includes destination, year and product code fixed effects and the average of the firm or countries regressors. Standard errors between parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The results are consistent with our priors regarding the impact of exchange rates on export participation: higher exchange rates lead to less participation in foreign markets since they increase the price faced by final consumers. Similarly, firms facing an increase in their importing costs, because of exchange rates movements, tend to decrease their export participation. Consistent with this mechanism, the effect is reduced for firms which import expenditures represent a large part of their costs. However, the effect of this interaction terms is not always of the expected sign, probably due to the strong collinearity between the different regressors. From this first step, we construct the inverse Mills ratio that is added as regressor in the utility function of the model. This addition controls for the endogenous selection in trade flows that shifts the distribution of the utility parameter ξ_{jdt} for the observed trade flows. We present the estimated parameters of the model in table 5.

In order to highlight the role played by the instruments and the specifications, we start by estimating the model without random coefficients, and with simple OLS. In the first two columns of table 5, we estimate a simple logit demand function, by regressing the logarithm

TABLE 5: Estimation results

	OLS		IV		RC
log price	0.40*** (0.01)	0.38*** (0.01)	−3.07*** (0.22)	−4.78*** (0.30)	
log price \times inc _d	0.52*** (0.01)	0.59*** (0.01)	0.30*** (0.07)	0.54*** (0.09)	
α					1.82*** (0.26)
Π_α					−0.11*** (0.04)
Σ_α					0.01 (6.1)
Σ_F					1.79** (1.02)
$\Sigma_{\alpha,F}$					−0.25 (0.38)
<i>Mills ratio</i>		0.51*** (0.02)		1.50*** (0.06)	1.32*** (0.14)
<i>Leather sole</i>	−1.0*** (0.01)	−1.1*** (0.01)	−1.21*** (0.02)	−1.60*** (0.03)	−1.64*** (0.22)
<i>Leather top</i>	1.18*** (0.02)	1.27*** (0.02)	0.81*** (0.03)	0.86*** (0.04)	0.91*** (0.11)
<i>Fabric top</i>	−0.02 (0.02)	−0.008 (0.02)	−0.010 (0.02)	0.050* (0.03)	0.003 (0.09)
<i>Boot</i>	−0.59*** (0.01)	−0.62*** (0.01)	−0.56*** (0.02)	−0.63*** (0.02)	−0.61*** (0.03)
First stage F-stat			67.2	51.8	

Notes: Number of observations: 175 766. Standard errors between parentheses. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

of the product market share on product characteristics. In the first column, we omit the Mills ratio, to highlight the importance of controlling for endogenous selection in trade flows. These specifications emphasize the importance of instrumenting prices to consistently estimate the model parameters. In the absence of instruments, we obtain a positive coefficients on prices, at odds with simple economic theory. Columns 3 and 4 from table 5 estimate the demand equations using our instruments to address the endogeneity of prices. These specifications give estimates of the price elasticity much more consistent with existing studies: for small firms in the market, the price elasticity is equal to 4.78 when controlling for selection by including the inverse Mills ratio. Moreover, the results show that consumers from richer destinations tend to have lower price elasticity, which is consistent with the idea that richer consumers are less sensitive to prices and therefore value relatively more high-quality, high-price products.

We now turn to the specification with random coefficients. An estimate of α of 1.82 implies an average price elasticity of $\exp(1.82) = 6.17$, consistent with the results obtained in the absence

of random coefficients. Moreover, this specification also captures the fact that richer consumers have a smaller price elasticity relative to others. Regarding other sources of heterogeneity, the model does not identify additional heterogeneity in price elasticity, besides the ones captured by income. However, the model identifies that some consumers prefer French goods over other goods. These consumers tend also to be less price sensitive than others. Overall, these results show important variations in consumers preferences, especially based on their income and their preference for French goods.

Regarding the role of other variables, we find consistent results across specifications. The coefficient on the Mills ratio is significant and positive, which confirms the importance of endogenous selection in explaining export participation. Moreover, all characteristics significantly affect the demand for the product.

5.2 Estimation outcomes

In order to shed more light on the implications of the introduction of random coefficients, we now describe the distribution of mark-ups, price elasticities and cross-elasticities with Chinese exports, that French firms are facing. These distributions highlight how accounting for different types of consumers have implications for firms regarding their relative market power, and their exposure to Chinese competition.

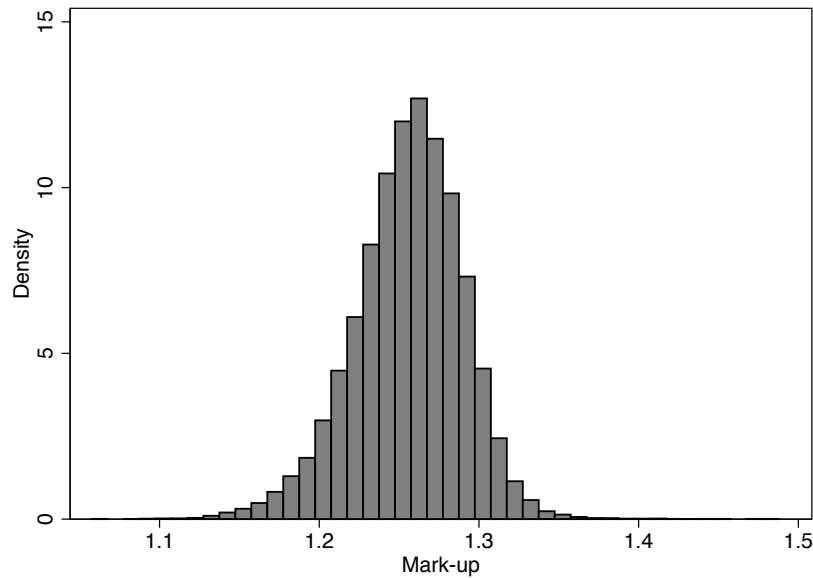


FIGURE 5: Distribution of mark-ups of French firms

Figure 5 displays the distribution of mark-ups for French firms for all the different markets they export to. Therefore, the unit of observation is a specific variety in a foreign market at a given time. A first element to point out is the relative consistency of these numbers with the existing literature. The average mark-up is around 25% which is in the ballpark of profit margin estimated in the Industrial Organization literature. Moreover, we find an important dispersion across firms with mark-ups varying from 15% to more than 30%.

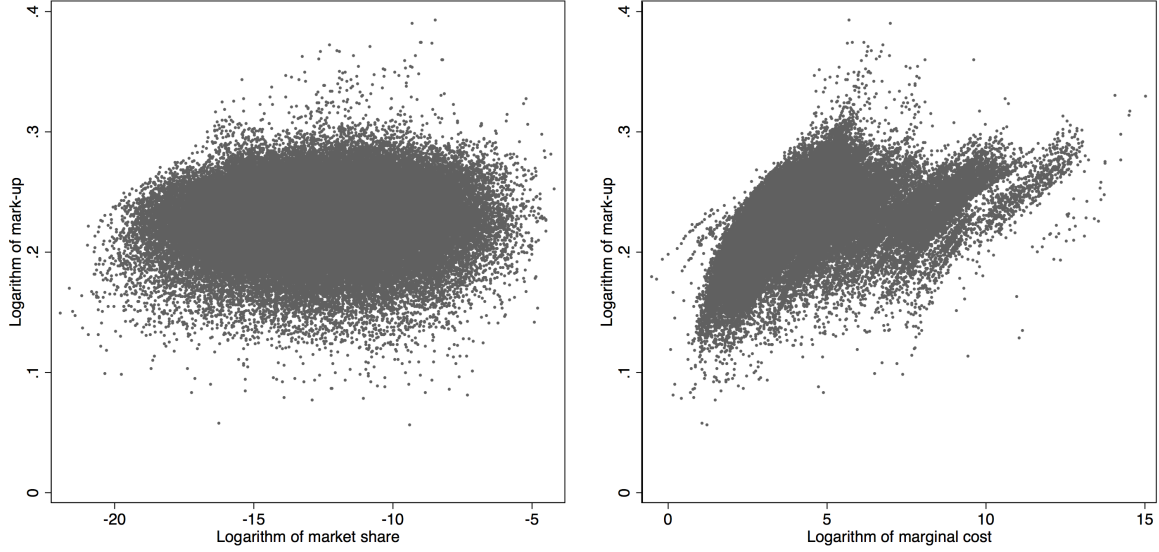


FIGURE 6: Correlation of mark-up with market share and marginal cost

In order to understand the sources of this variation in mark-up, we regress its logarithm to the two main sources of variation in price-elasticity: the market-share of the variety and its marginal cost. From equation (3), the mark-up of the firm is a function of its market share, and of the price elasticity of its average consumer.

Figure 6 displays the scatter plots between these three variables. We notice that a significant amount of the variation in profit margin comes from the position of the firm in the price distribution: firms with smaller marginal costs, tend to have much smaller mark-ups. The reason for this is that firms which produce low-quality products at low prices have consumers that are much more price-sensitive. Therefore, it is optimal for them to set a small price for their product. On the contrary, firms with higher marginal costs face consumer with lower dis-utility from high prices and can therefore set higher mark-ups.

This heterogeneity can also be highlighted by showing variations in the average price-elasticity faced by French firms. In figure 7, we display the distribution of the average price-elasticity faced by French firms in different markets. This average price-elasticity is obtained from the individual consumer's price-elasticity weighted by their individual market share in each good, and their total expenditures for shoes. We can see from the figure a large dispersion in price-elasticity ranging from 4 to 7. This dispersion similarly reflects the fact that firms face very different average consumers, affecting their optimal response in terms of prices.

In addition to generating variations in mark-ups, the existence of heterogeneous consumers has a second important consequence: consumers who care more about prices are also consumers who spend a large share of their income in goods produced by other low-cost producers. Therefore, firms with low prices are specifically selling to consumers who are likely to turn to Chinese producers, given their preference for low-price products. To emphasize this heterogeneity, we measure the cross-price elasticity of each French firm with regards to Chinese exports. In other words, how much their market shares would increase, should the price of Chinese firms increase. Results are displayed in figure 8.

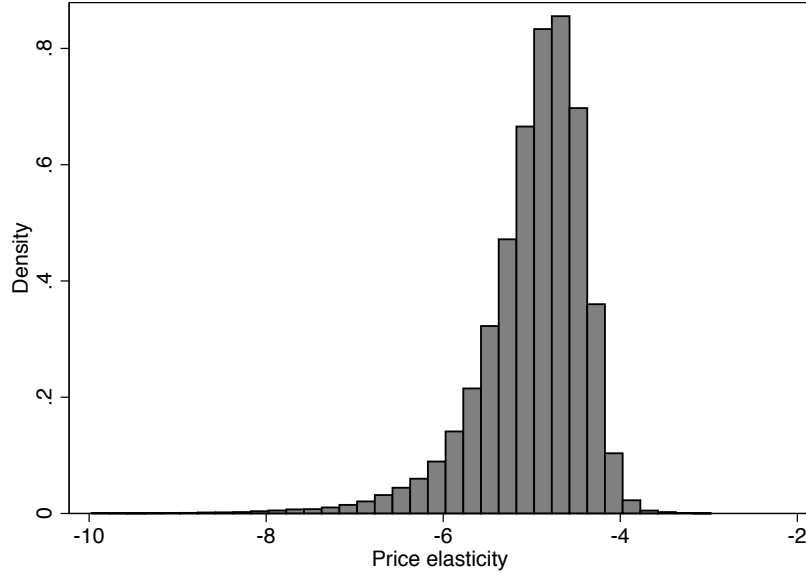


FIGURE 7: Distribution of price elasticity (French firms)

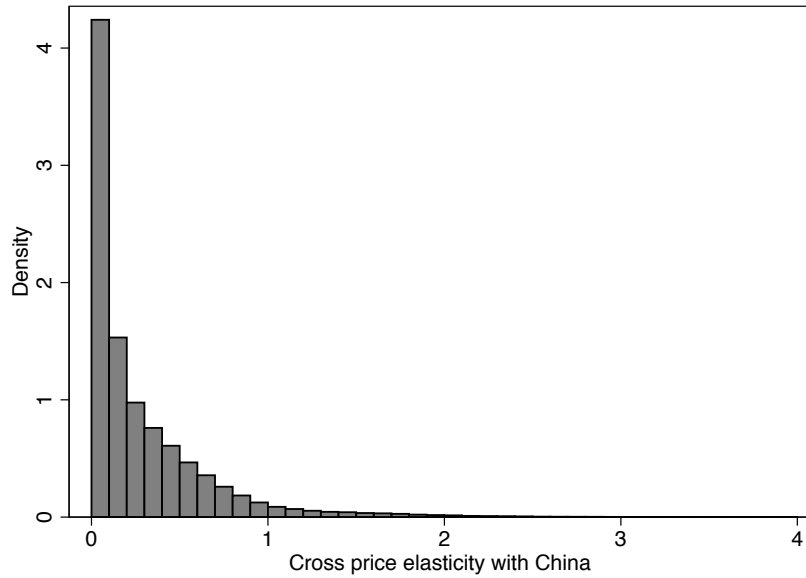


FIGURE 8: Distribution of cross price elasticity with Chinese exports

We can see from figure 8 that French firms are very differently affected by a change in Chinese firms' prices. A large share of French firms are barely affected by a change in Chinese prices. On the contrary, some firms have a cross-price elasticity larger than one, emphasizing their strong connection with Chinese products: since these firms share a large fraction of their consumers with Chinese firms, they would see significant gains in market shares if Chinese firms were receiving a negative shock.

This heterogeneity in cross-price elasticities has implications for the quality response to the China shock. According to the model, firms producing low-quality products at low price should suffer more from the rise of Chinese competition. As a consequence, it becomes over time relatively more profitable to produce higher quality products. Therefore, we should observe that

the relative quality of low-price firms increases over the period, as they intend to escape Chinese competition. This prediction is confirmed by figure 9 that reports the relative average quality of French exporters over time, depending on their position in the price distribution in 1997¹⁵. As expected, each quartile has been bridging some of the quality gap to the upper quartile, which is consistent with model prediction.¹⁶

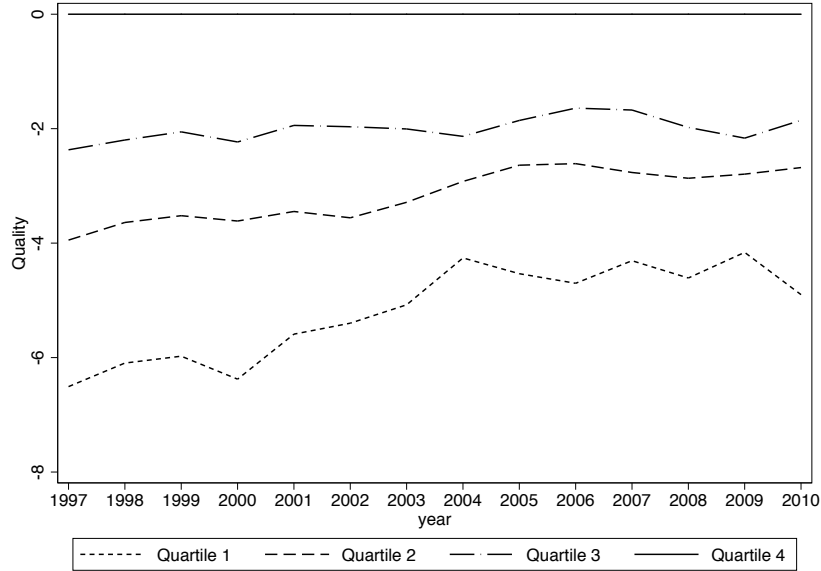


FIGURE 9: Low Price Varieties Upgrade their Quality over the Period

5.3 Supply-side estimates

After having estimated the demand system, we can now obtain measures of marginal costs of all products by subtracting the estimated mark-ups from the observed prices. Therefore, we can regress these estimated marginal costs on product characteristics and quality to recover the cost elasticity of each characteristic. Table 6 displays these estimated parameters.

We start by regressing the logarithm of the marginal cost on the estimated measure of quality and observed characteristics without instrumenting the product quality. Column 1 shows that we observe a positive correlation across French firms between the marginal cost of production and the quality of the product. Similarly, column 2 shows a similar positive correlation when including firm-destination fixed effects: when a firm increases the quality of its product in a destination, the marginal cost of production increases. However, the cost-elasticity of quality is smaller when estimated within rather than across firms: the elasticity is 0.17 across firms while it is 0.12 when looking at within-variation across time. Moreover, column 3 shows that

¹⁵In order to build this graph, we broke down into price quartiles the population of French exporters on each market in 1997. Then we computed the mean across all destination markets, by quartile-year, of individual qualities. Finally, for each year, we normalized the average quality of the top quartile to zero.

¹⁶Notice that the quality estimates used in figure 9 are obtained from estimating the demand side of the model only. In that sense, the figure is not obtained by “forcing” low-price firms to behave optimally and upgrade their quality in response to Chinese competition.

this relationship is slightly convex: adding a quadratic term for quality returns a significant parameter of 0.0005 which signals some convexity in the impact of costs on quality.

TABLE 6: Estimation results: marginal costs

	OLS			IV	
λ	0.17*** (0.004)	0.12*** (0.002)	0.13*** (0.006)	0.17*** (0.005)	0.44*** (0.04)
λ^2			0.0005* (0.0002)		0.009*** (0.001)
<i>Leather sole</i>	0.50*** (0.02)	0.32*** (0.01)	0.31*** (0.01)	0.29*** (0.02)	0.22*** (0.03)
<i>Leather top</i>	0.87*** (0.03)	0.44*** (0.02)	0.44*** (0.02)	0.48*** (0.02)	0.52*** (0.02)
<i>Fabric top</i>	0.22*** (0.03)	0.13*** (0.02)	0.13*** (0.02)	0.12*** (0.02)	0.12*** (0.02)
<i>Boot</i>	-0.03 (0.02)	0.03*** (0.009)	0.03** (0.009)	0.02** (0.01)	0.02** (0.01)
N	99 353	93 511	93 511	93 511	93 511
First stage F-stat				651	17.8
Firm-destination FE	N	Y	Y	Y	Y

Notes: The dependent variable is the logarithm of marginal cost. Firm-level clustered standard errors between parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

As mentioned in the previous section, the endogenous nature of product quality casts some doubts on the structural estimates identified from correlation between marginal costs and quality measures. To address this issue, columns 4 and 5 in table 6 shows the estimated elasticities using as instrument the change across time in the nature of competition faced by French firms. Column 4 reports the elasticity obtained when assuming a linear relationship between the logarithm of marginal costs and quality. The estimated elasticity (0.17) is larger than the one obtained using OLS. This result reflects the complementarity between productivity and quality choice: in the data, firms adjust their quality when it is relatively affordable to do so. Therefore, a change in quality for exogenous reasons generates a larger increase in marginal costs than measured without instruments. Moreover, column 5 shows that instrumenting also reveals a strong convex relationship between quality and marginal costs: as quality increases, the impact on marginal costs becomes larger. Finally, the validity of this instrumental variable strategy is confirmed by the Kleibergen-Paap F-statistic of the first stage regression, which is larger than the threshold used to rule out the presence of weak instrument.

In order to confirm the shape of the relationship between marginal cost and quality, we report a scatter plot in figure 10. To construct this figure, we regress the log of the marginal

cost on variety-destination fixed effects and product characteristics, and use the residual of this regression as a measure of normalized marginal costs. Similarly, we regress the measured quality on a similar set of fixed effects and our instrument for quality, to obtain the residual as normalized instrumented quality. Figure 10 displays the scatter plot of these two measures.

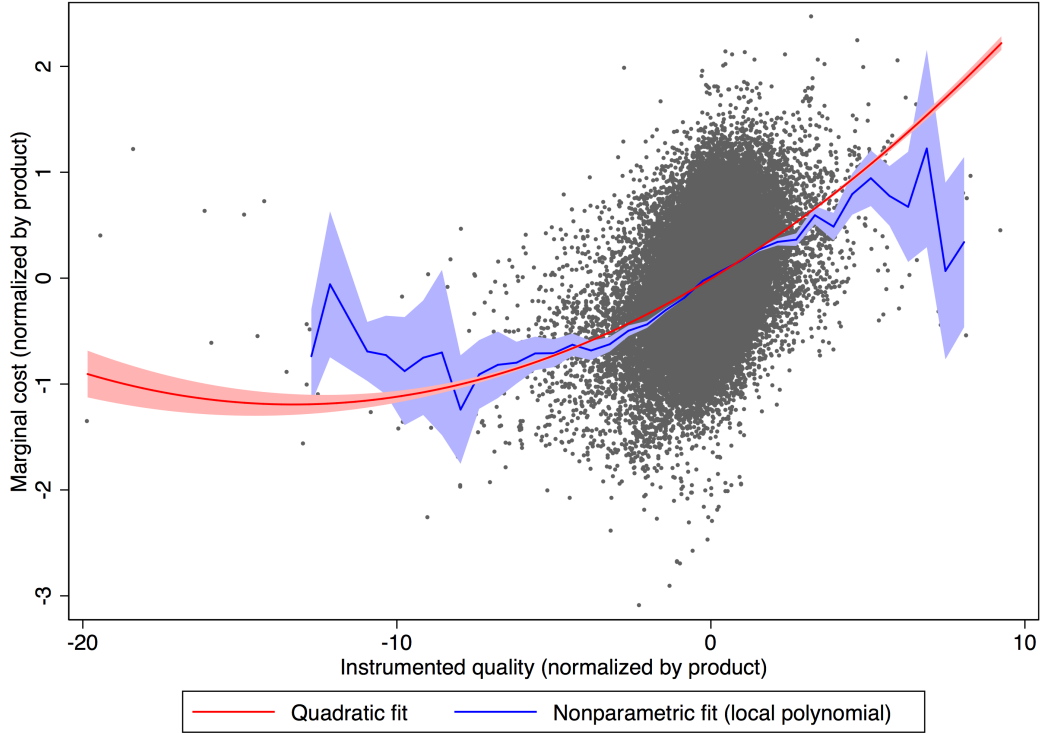


FIGURE 10: Relationship between marginal cost and product quality

Figure 10 confirms the convex relationship between costs and quality. The red line reports the fit and its confidence interval from a second order polynomial between the logarithm of marginal cost and instrumented quality. In order to check the robustness of this relationship, we report in blue a non-parametric regression between costs and quality, estimated using local polynomials. The comparison of these two predictions shows that the use of a polynomial of order two is reasonable to capture the relationship between marginal costs and quality. As a consequence, we use the coefficients obtained in the last column of table 6 to parametrize the marginal cost function in the counterfactual exercise performed in the next section.

6 Counterfactuals

Having estimated a model of demand and supply for the shoes industries, we can now simulate a range of experiments and report their consequences on French firms. As highlighted throughout the paper, we are particularly interested in the impact of the surge of Chinese competition in foreign markets, and in particular how differently French firms have been impacted by this rise in Chinese exports. In this section, we therefore implement the following experiment: what would

have happened if the 1997-2010 exports of Chinese firms had stayed at their level of before 2001, the year they entered the WTO? In answering this question, we want to emphasize two elements. First, how heterogeneous are the effects of this shocks along the price ladder. Second, to which extent the ability of upgrading their products has allowed French firms to mitigate the effect of the China shock. We first describe the case in which firms are unable to adjust their product quality. Then, we study how the ability to choose their quality allows French firms to mitigate the impact of the China shock.

6.1 Without quality adjustment

The growth of Chinese exports during the sample period is mainly due to an increase in the demand shifter of their exports, the variable $\xi_{f dt}$, that measures the unobserved components entering consumer utility. Therefore, our experiment consists in setting this variable to its average over the years 1997-2000 for Chinese producers, in each market and destination they export to.

In the absence of adjustment of the extensive margin, performing the experiment is quite straightforward. However, it is still necessary to solve for the optimal mark-up charged by firms under the new market conditions. We use as inputs in this counterfactual the objects delivered by the estimation: parameters estimates, measures of quality ($\lambda_{f dt}$) and marginal costs ($c_{f dt}$) for each producer. With these objects in hand, we can solve for the equilibrium prices by solving iteratively for the optimal mark-up charged by firms, and the market shares induced by these prices. We successively update prices and market shares using equations (2) and (3) until we reach a fixed point that defines the equilibrium.

We can then compare this new equilibrium with the one observed in the data. Specifically, we compare firms outcomes depending on their position in the price distribution. For each observation, we compute the log-deviations of market share, profit and mark-up and report the median of these changes in 2010 by price deciles.¹⁷ Results of this experiment are displayed in figure 11.

Figure 11 shows that all French firms gain from the reduction of the quality of Chinese exports in foreign markets. Moreover, firms are differently affected by this change: the first decile in the price distribution sees a 10 percent median increase of their market share, while the tenth decile records a 3 percent median increase. This result comes directly from the presence of heterogeneous consumers. Consumers who value low prices and therefore consume Chinese goods, report their consumption on affordable French goods rather than on expensive ones. However, it is important to note that all French varieties significantly increase their market shares, including the most expensive ones. As a consequence of this increase in market shares, we can see that profits of French firms in foreign markets increases too. There is once again substantial heterogeneity with a median increase of 9 percent for the first decile and less than three percent for the tenth decile.

Turning to the change in mark-ups, we see that all firms tend to reduce their mark-ups. This might seem a surprising result, given that a reduction in Chinese export quality should lower competitive pressure. However, this is in line with the predictions of the model: when Chinese

¹⁷Figure 17 in the appendix displays the entire distribution of log-change across the price distribution.

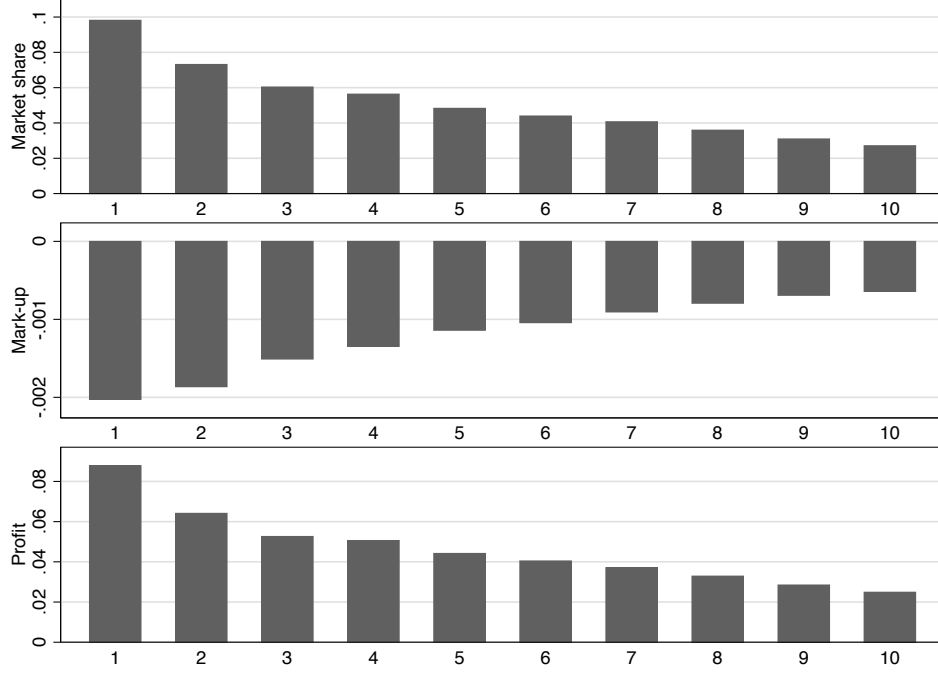


FIGURE 11: Effect of a reduction in Chinese exports by price deciles (on French firms in 2010)

export decrease, consumers with preference for low prices start to buy more French goods. As a consequence, the average consumer of French goods, is more price sensitive than it used to be. Therefore, French firms find it optimal to reduce their prices to capture these new consumers that used to buy Chinese goods.

These heterogeneous gains in market shares reflect the fact that it becomes much more profitable to be a low-price firm after the reduction of Chinese exports. Therefore, the change in Chinese competition changes the relative benefit of high quality. As a consequence, we should expect significant adjustment in terms of product quality following this change in market conditions. We present the results taking into account this source of adjustment in the next section.

Accounting for endogenous quality Allowing for quality changes means that the mark-up charged by a firm, its product quality and therefore its marginal costs are all variables that will change because of the experiment. To find this equilibrium, we rely on two first-order conditions: the ones obtained for price setting, equation (3), and equation (5) related to the quality level. Therefore, from the observed or estimated objects (mark-ups, marginal costs and quality) the new equilibrium is obtained by iterating the following steps until convergence:

- From product qualities and marginal costs, set the mark-ups based on the pricing first-order condition:

$$p_{jdt} = \left(1 + \frac{1}{\int (1 - \mathbb{P}_{jdt}(y, \nu)) \exp(\alpha(y, \nu)) \omega_{jdt}^{(2)}(y, \nu) dy d\nu} \right) c_{jdt}.$$

- From mark-ups and prices, we can update the optimal quality. From the first order condition (5), and assuming that $h(\cdot)$ is a polynomial of order 2, we have $\frac{\partial \ln c}{\partial \lambda} = h_1 + 2h_2 \lambda_{fdt} + \eta_{jdt}$

such that

$$\lambda_{fdt} = \frac{1}{2h_2} \left(\frac{1}{\int \exp(\alpha(y, \nu)) \omega_{jdt}^{(3)}(y, \nu) dy d\nu} - h_1 - \eta_{jdt} \right).$$

- Given the new quality, obtain the new marginal cost from the function:

$$\ln c_{jdt} = h_1 \lambda_{jdt} + h_2 \lambda_{jdt}^2 + x_{jdt} \rho + \eta_{jdt} \lambda_{jdt} + \varphi_{jdt}$$

In order to run this algorithm, it is necessary to obtain estimates for h_1 and h_2 , but also calibrate values of φ_{jdt} and η_{jdt} . We use estimates from section 5 that gives us values of 0.44 and 0.0085 for respectively h_1 and h_2 . Regarding the calibrated parameters, we rely on the optimality conditions to infer their values from observed qualities. Specifically, we use the two following equations:

$$\begin{aligned} \eta_{jdt} &= \frac{1}{\int \exp(\alpha(y, \nu)) \omega_{jdt}^{(3)}(y, \nu) dy d\nu} - h_1 - 2h_2 \lambda_{fdt} \\ \varphi_{jdt} &= \ln c_{jdt} - h_1 \lambda_{jdt} - h_2 \lambda_{jdt}^2 - x_{jdt} \rho - \eta_{jdt} \lambda_{jdt}. \end{aligned}$$

Having in hand these measures, we can now turn to the counterfactual experiment. Since we allow firms to adjust their quality, we can now study the impact of the rise in Chinese exports, rather than the decrease in the previous paragraph. To understand why, consider the equilibrium as the object E that depends on the level of Chinese competition (C_L or C_H), and the product quality of French firms $q(C)$ that depends on this level of competition. As such, the equilibrium in the data can be referred as $E(C_H, q(C_H))$.¹⁸ Therefore, we start by solving for the equilibrium in which French firms adjust their quality to a low level of competition, $E(C_L, q(C_L))$. Then, we compare this initial equilibrium to $E(C_H, q(C_L))$, the scenario in which French firms cannot adjust their quality, and to $E(C_H, q(C_H))$, which allows for quality adjustments. Therefore, we measure by how much quality adjustments allowed firms to mitigate the impact of the rise in Chinese competition. Figure 12 displays the effects of Chinese exports on French firms under those two scenarios.

First of all, we see that the effects are symmetric relative to the previous experiment: firms at the bottom of the price distribution suffered more from Chinese competition relative to the ones at the tops. Looking at profits, we see a difference of roughly one to five between the median effects for the first decile relative to the tenth decile. Second, we see important adjustments in terms of quality, driven by firms at the bottom of the price distribution. Surprisingly, this quality adjustment amplifies the losses in market shares due to the China shock. The reason for this result is that French firms decide to move up the quality ladder, reducing the scale of their production through higher mark-ups. As a consequence, quality upgrading reduces further market shares of French firms, but limit the profit losses of firms at the bottom of the price distribution.

However, the quality responses of French firms appears to have a limited effect on profits.

¹⁸In the previous paragraph, we compared the equilibria $E(C_H, q(C_H))$ and $E(C_L, q(C_H))$

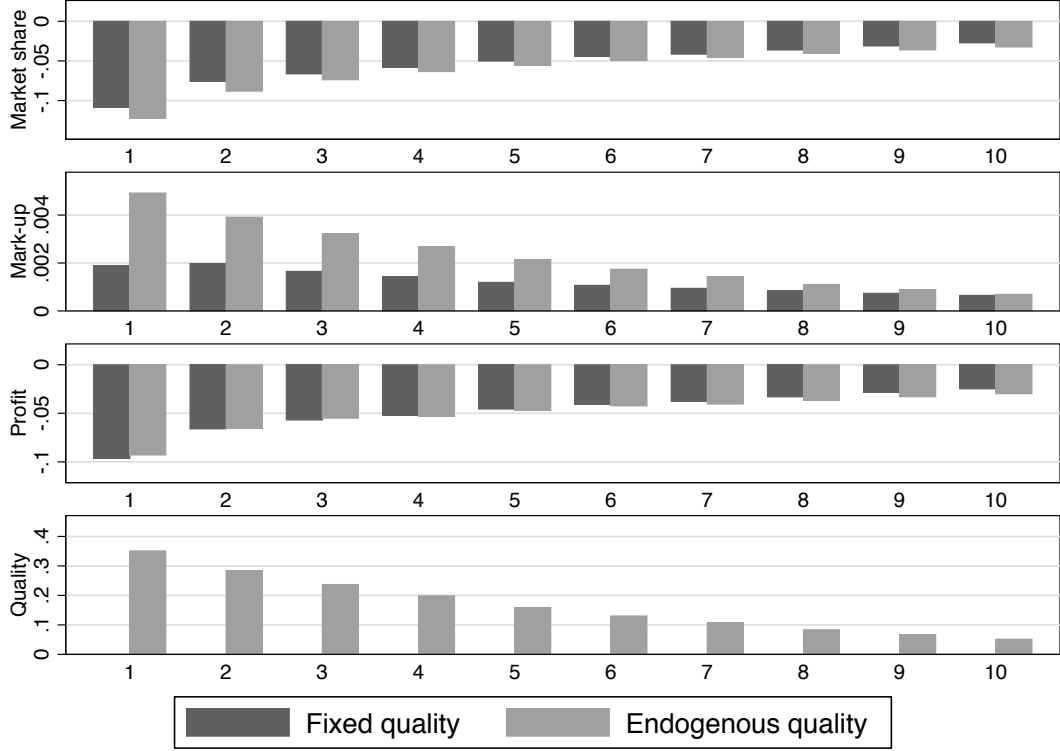


FIGURE 12: Effect of an increase in Chinese exports by price deciles (on French firms in 2010)

In fact, only firms at the bottom of the price distribution limit their losses by upgrading their quality but to a very limited extent. Moreover, firms located higher in the price distribution actually lose more profit when firms are able to adjust their quality. The reason for this result is that the quality response of low-price firms creates a ripple effect on higher price firms: while these firms are less affected by Chinese competition directly, they lose additional profit from the increasing competition of French firms which upgrade their products. Overall, the quality response does little to limit the effect of low-cost competition. The cost of quality upgrading is large enough that firms still suffer significant losses despite the possibility of upgrading their products. It indicates that this mechanism only offers limited relief for firms aiming at mitigating the adverse effects of low-cost countries competition.

To conclude the description of our counterfactual experiment, we describe the aggregate impact of the increase in Chinese competition on French exports. Figure 13 describes the total exports of shoes from our sample in three scenarios: the case in which China keeps its exports characteristics from before 2001 (baseline), total exports when accounting for the rise of China (red line), and the scenario in which China rises and French firms can adjust their quality (blue line).¹⁹

Figure 13 shows the negative impact of the China shock on French shoe exports. At the end of the sample period, French exports are reduced by roughly 150 millions US dollars annually. The figure also highlights that the quality response of French firms had a very small impact on the impact of the China shock: the scenario with quality upgrading has slightly larger exports but the difference between the two scenarios is very limited. This confirms the previous conclusion

¹⁹Therefore, the blue line is the scenario which took place in reality.

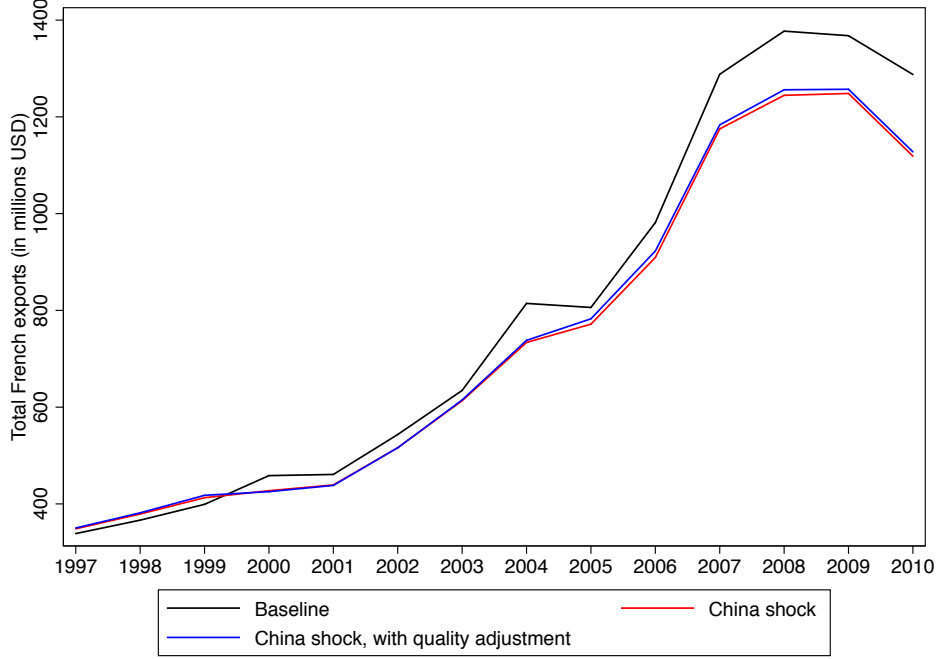


FIGURE 13: Impact of the China shock on French shoe exports

that quality upgrading did little to help French firms escape Chinese competition.

7 Conclusion

In this paper, we quantify the heterogeneous impact of Chinese competition along the quality ladder. To achieve this, we estimate an oligopolistic model of international trade in which consumers' preferences are heterogeneous. In particular, we allow the price elasticity to vary across consumers, which generate stronger substitution patterns across firms that are located closely to each other in the price distribution. Moreover, we allow firms to endogenously choose their product quality, allowing them to sell larger quantities at the expense of higher marginal costs of production.

Estimating the model using export data from the footwear industry, we find evidence of heterogeneity in consumers' preferences: rich consumers are less sensitive to prices, and display higher preferences for French goods. These results imply that a French firm is closer substitute to another French variety relative to a foreign variety, but also that this firm has stronger substitution patterns with producers with similar prices. The estimation also allows us to quantify the impact of product quality changes on marginal costs of production: we find that changes in quality are associated with increasing and convex marginal costs of production.

We then proceed to quantifying the impact of the rise in Chinese competition by reducing the Chinese exports to their pre-2001 level. Our counterfactual experiment shows that French firms at the bottom of the price distribution lost much more than those at the top: at the first decile of the price distribution, the median firm reduces its market shares by 10 percent, while firms at the top only lost 2 percent. Moreover, having estimated the marginal costs associated with product quality changes, we can quantify the potential quality response from French exporters.

We find that the quality response of French firms did little to mitigate the impact of Chinese competition.

These results shed light on the presence of heterogeneous impact of the Chinese competition, even within a specific affected industry. Moreover, we show that the possibility to upgrade its product does little to help firms: firms at the bottom of the price distribution are relatively less efficient at producing quality in the first place, and upgrading its quality is a costly process. Therefore, it does not appear to be a profitable way-out for the firms the most severely impacted in our setup. In the future, we also intend to assess how the consequence of China on the vertical differentiation of French firms ultimately impacts skilled and unskilled workers. Since, high-quality firms tend to be intensive in skilled workers, we expect this mechanism to amplify the unequal impact of international trade across workers.

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Appendix

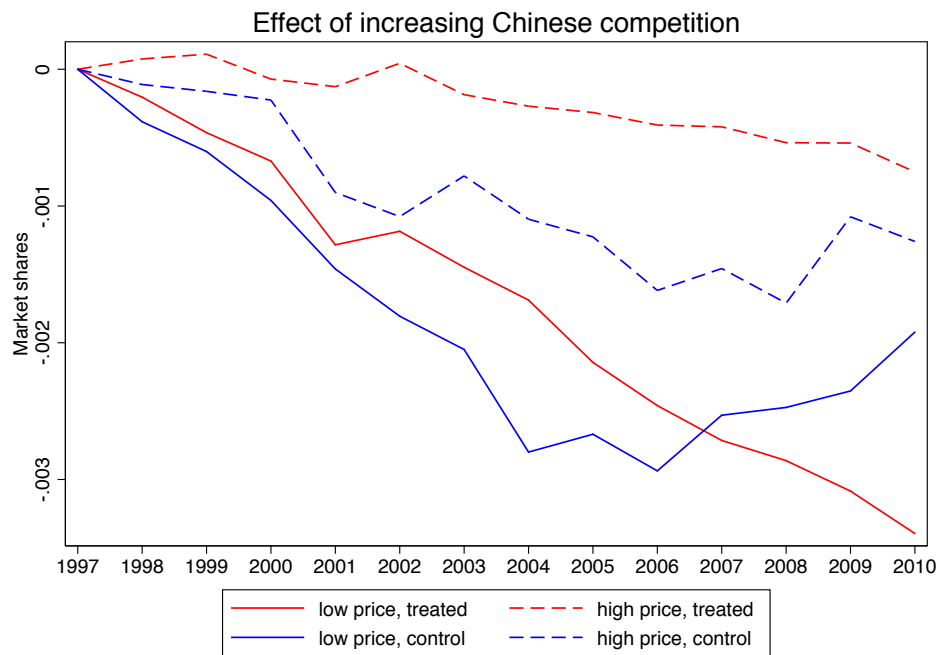


FIGURE 14: The China Shock Impacts Low-Price Varieties More

Notes: This figure shows the change in the market share, $s_{fdpt} - s_{fdp97}$, averaged at the group-year level, for four different groups of export flows: control-low price; control-high price; treated- low price; treated- high price.

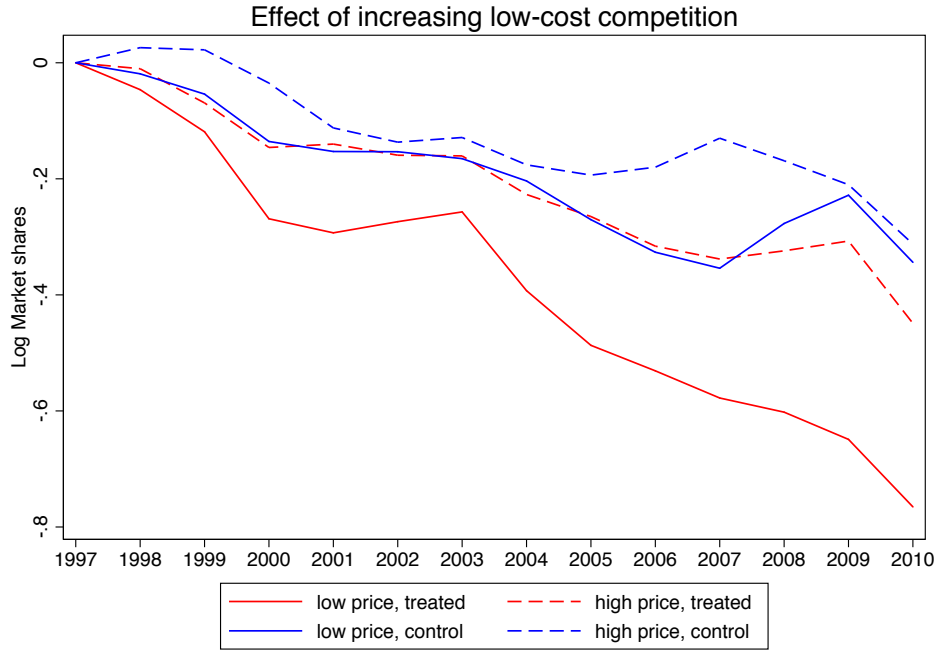


FIGURE 15: Low-cost competition Impacts Low-Price Varieties More

Notes: This figure shows the change in the log market share since 1997, $\ln s_{fdpt} - \ln s_{fdp97}$, averaged at the group-year level, for four different groups of export flows: control-low price; control-high price; treated- low price; treated- high price. Control and treatment groups are computed based on the change in market shares of low-cost countries.

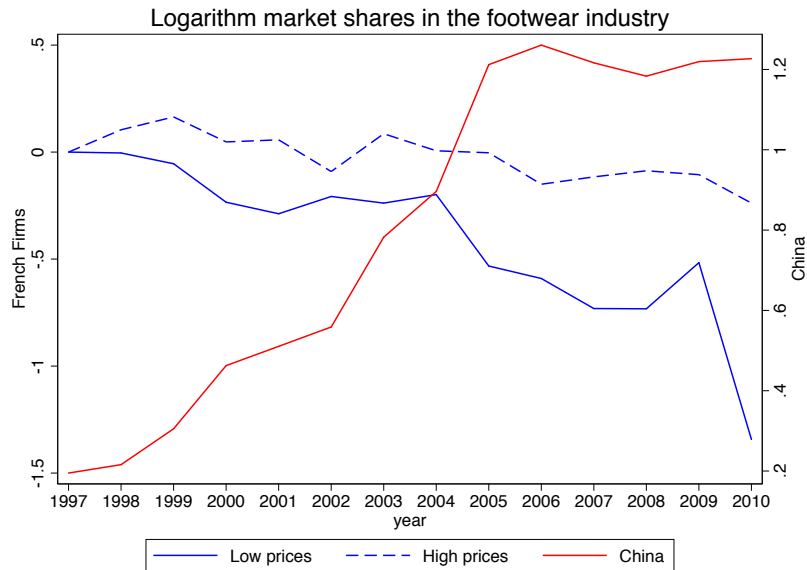


FIGURE 16: The China Shock Hits Cheap Shoes Harder

TABLE 7: Selection of product codes

Product code	Description	Included	Characteristics			
			Boot	Top leather	Sole leather	Top fabric
640110	Waterproof footwear incorporating a protective metal toecap	No				
640192	Waterproof footwear covering the ankle	No				
640199	Waterproof footwear covering neither the ankle nor the knee	No				
640212	Ski-boots, cross-country ski footwear and snowboard boots	No				
640219	Sports footwear with outer soles and uppers of rubber or plastics	No				
640220	Footwear with outer soles and uppers of rubber or plastics, with upper straps or thongs assembled to the sole by means of plugs	No				
640291	Footwear covering the ankle, with outer soles and uppers of rubber or plastics	Yes	1	0	0	0
640299	Footwear with outer soles and uppers of rubber or plastics	Yes	0	0	0	0
640312	Ski-boots, cross-country ski footwear and snowboard boots, with outer soles of rubber, plastics, leather or composition leather and uppers of leather	No				
640319	Sports footwear, with outer soles of rubber, plastics, leather or composition leather and uppers of leather	No				
640320	Footwear with outer soles of leather, and uppers which consist of leather straps across the instep and around the big toe	No				
640340	Footwear, incorporating a protective metal toecap, with outer soles of rubber, plastics, leather or composition leather and uppers of leather	No				
640351	Footwear with outer soles and uppers of leather, covering the ankle	Yes	1	1	1	0
640359	Footwear with outer soles and uppers of leather	Yes	0	1	1	0
640391	Footwear with outer soles of rubber, plastics or composition leather, with uppers of leather, covering the ankle	Yes	1	1	0	0
640399	Footwear with outer soles of rubber, plastics or composition leather, with uppers of leather	Yes	0	1	0	0
640411	Sports footwear, incl. tennis shoes, basketball shoes, gym shoes, training shoes and the like	No				
640419	Footwear with outer soles of rubber or plastics and uppers of textile materials	Yes	0	0	0	1
640420	Footwear with outer soles of leather or composition leather and uppers of textile materials	Yes	0	0	1	1
640510	Footwear with uppers of leather or composition leather	No				
640520	Footwear with uppers of textile materials	No				
640590	Footwear with outer soles of rubber or plastics, with uppers other than rubber, plastics, leather or textile materials; footwear with outer soles of leather or composition leather, with uppers other than leather or textile materials; footwear with outer soles of wood, cork, paperboard, furskin, felt, straw, loofah, etc.	No				
640610	Uppers and parts thereof	No				
640620	Outer soles and heels, of rubber or plastics	No				
640690	Parts of footwear; removable in-soles, heel cushions and similar articles; gaiters, leggings and similar articles, and parts thereof	No				

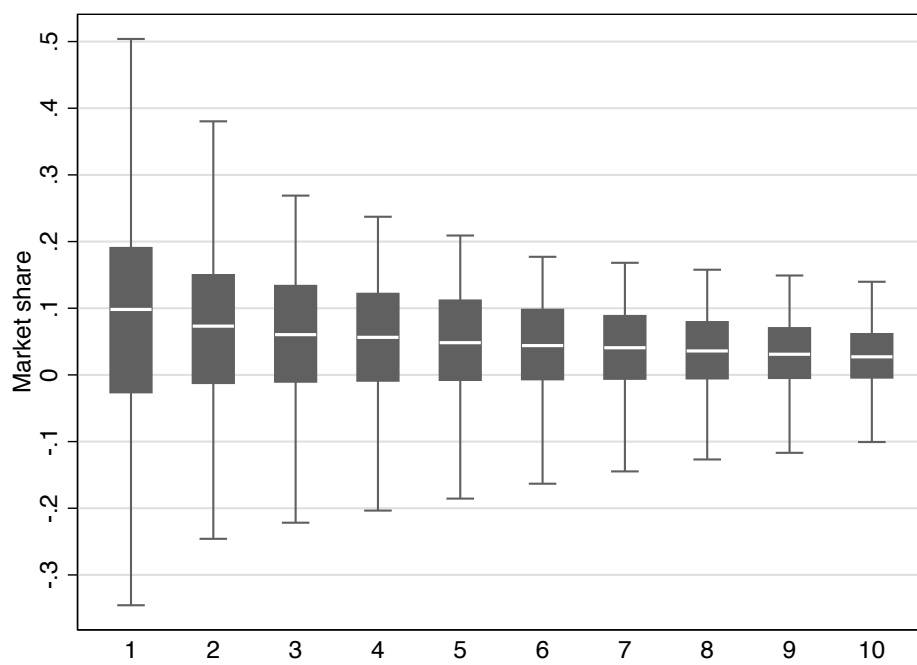


FIGURE 17: Effect of a reduction in Chinese exports by price deciles