Foreign Competition along the Quality Ladder*

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Abstract

We document that French firms with low prices are more affected by the rise of low-cost competition relative to high-price firms. To rationalize this finding, we propose a random-coefficients demand model in which consumers have heterogeneous preferences. This heterogeneity generates rich substitution patterns across producers and leads firms to upgrade their product quality in response to low-cost competition. We estimate the model using data from the footwear industry, and use it to quantify the unequal impact of the "China shock". We find that Chinese competition was twice more damaging to French firms at the bottom of the price distribution relative to firms at the top. Moreover, we show that allowing firms to adjust their quality to mitigate the effect of the shock did little to help them escape low-cost competition.

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1 Introduction

One of the most salient changes of the last twenty years has been the rapid integration of large developing countries in the global economy. The participation of these countries with low cost of production has contributed to unprecedented levels of product diversity and low prices for consumers, but has also had important disruptive effects on manufacturing industries in developed economies. While the impact of this global integration on different industries has been extensively studied, little has been said on the heterogeneous effects of this competition across firms: most international trade models assume Constant Elasticity of Substitution (CES) preferences such that all products, within a defined industry, are equally affected by changes in competition.[1]

In this paper, we argue that firms have not been equally impacted by the increasing competition from low-cost countries. We develop and estimate a model of demand in which consumers are heterogeneous in their preferences for product characteristics, including prices. As a result, varieties with similar characteristics are closer substitutes because they compete over consumers with similar preferences. Therefore, our model can measure to which extent firms producing low-quality goods are more affected by the rise in low-cost competition than firms producing high-end products. Moreover, these rich substitution patterns imply that an increase in low-cost competition generates an "escape-competition" effect: firms will have incentives to upgrade their product quality as a result of higher relative profit from high-quality goods. Our empirical strategy measures the cost of producing higher quality good and shows that this quality response did little to mitigate the impact of low-cost competition.

We start by showing reduced form evidence of the heterogeneous impact of low-cost competition across firms. Using firm-level data from France and product-level data from 38 foreign countries, we show that French firms with low prices had lower performance records in markets where the import penetration from low-cost countries increased. Specifically, they display larger reductions in exported values and survival rates in these markets relative to higher price firms. Symmetrically, increases in the market shares of developed countries have a larger impact on firms producing high-price goods. Overall, French exporters are disproportionately more affected by competing firms that resemble them.

Based on this evidence, we develop an empirical model in which consumers have heterogeneous preferences and firms choose their optimal product quality. On the demand side, we follow Berry, Levinsohn, and Pakes (1995) and use random coefficients to introduce heterogeneity in consumers' preferences over product characteristics. We assume a continuum of consumers in each destination market, whose preferences can vary with their income and other unobservables characteristics, and aggregate these preferences using the income distribution in these foreign markets and distributional assumptions

[1] The use of nested CES demand or discrete choice models can reduce these stark patterns of substitution but only in very limited ways.

on the unobservables. A direct implication of this heterogeneity is to create substitution patterns across varieties that depend on their proximity in the product space. For instance, low-cost varieties will be more substitutable to cheap French varieties. Intuitively, all low-cost producers serve the same price-sensitive consumers. Therefore, when low-cost firms from developing countries enter a market, price-sensitive consumers switch to these varieties, which happens mostly at the expense of low-cost French producers. On the supply side, we allow firms to endogenously adjust the quality of their product. Producing higher quality goods comes at a higher marginal cost such that firms trade-off between serving a cheap product (price competitiveness) and serving an appealing product (non-price competitiveness).

To estimate the model, we combine French firm-level trade data and country-level trade data from 38 countries for the footwear industry between 1997 and 2010. We focus on the footwear industry because it produces a well-defined good, and resembles in many aspects the manufacturing sectors that suffered from the rise of low-cost competition. We estimate the demand system separately, using export values and prices of French firms and countries in 38 destination markets from the World Input Output Database.[2] Using international trade data to estimate this demand system has several advantages. First, it provides natural instruments to address the endogeneity of prices: we use exchange rates on exports to instrument country-level prices and average exchange rates on firms' imports to instrument firm-level prices.[3] Second, the use of international trade data facilitates the identification of the random coefficients by providing large variation across destinations in income distributions and in the cross-elasticity between low and high-cost varieties. Therefore, with the same data requirements as existing papers estimating demand in international trade, we can capture this heterogeneity in preferences from variations in income distributions across destination markets.

Introducing heterogeneity in preferences also allows us to estimate the cost of producing high-quality products, which is crucial to quantify the quality response to changes in competition. From the demand estimation, we can recover measures of product quality - defined as an unobserved utility shifter conditional to observed product characteristics - and of marginal costs (using the mark-ups derived from the demand system). However, estimating the cost of quality presents identification challenges: firms are likely to invest in quality when it is affordable to do so, such that a naive regression of marginal costs on quality is likely to underestimate the true impact of quality on marginal costs. Fortunately, our model delivers an instrument for quality: because the effects of competition are heterogeneous along the quality ladder, changes in the competitive environment modifies the first-order condition of the quality decision. Therefore, we can construct an instrument that captures exogenous changes in quality and identify the resulting cost of

[2]We restrict our sample to the 38 destinations contained in the WIOD dataset because it contains information about the domestic penetration rate in these destinations, which will be used as outside good in our model.

[3]See Piveteau and Smagghue (2018) for a description of this instrument.

higher quality from this exogenous variation.

The estimation results confirm the existence of heterogeneous consumers. We find that the heterogeneity in price-elasticity is particularly related to consumer income: as expected, richer consumers display lower price-elasticity of demand. As a consequence, we find significant differences in the mark-ups charged by French firms, ranging from 40 to 80 percent: firms with high costs serve inelastic consumers and therefore charge high markups. Moreover, we find heterogeneity across firms in their cross-elasticity with varieties from low-cost countries such as China. While cross-elasticity with Chinese products is close to zero for many firms, some firms' cross-elasticity are larger than one, indicating a strong substitutability with varieties from low-cost countries. These firms 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 also allows us to shed light on the quality decisions of French firms. We first document that the qualities of French exporters have converged during the sample period: firms with low product quality in 1997 record a larger growth of their quality over time, which is consistent with quality upgrading as a response to the increasing low-cost competition. Second, the estimation results validate our instrumental variable strategy when estimating the cost of quality: the measured quality-elasticity of marginal costs almost doubles when using our model-based instrument relative to the OLS estimate. Moreover, the relationship between quality and cost appears increasing and convex, such that the cost-elasticity to quality increases with the initial level of quality.

Finally, as a natural application of our model, we characterize the effect of the "China shock" on French firms. Having estimated the demand system and the cost of adjusting quality, we can quantify the heterogeneous impact of Chinese competition along the quality ladder, and the extent to which French firms mitigated this shock through quality upgrading. In particular, we compare the realized scenario to a counterfactual one in which Chinese exports maintained their characteristics from before 2001. The result of this experiment confirms the heterogeneous impact of the China shock along the quality ladder. We find that changes in market shares are twice larger at the bottom of the price distribution relative to the top: increase in Chinese competition generates a median 20 percent loss in market shares for the first decile in the price distribution. Meanwhile, firms in the highest price decile records a median 12 percent loss. Moreover, we find that the ability of firms to upgrade the quality of their product did little to help them mitigate this shock. Allowing firms to upgrade quality reduces the impact of Chinese competition by 5 percent for the lowest price decile. Moreover, the quality upgrading by low-quality firms implies stronger losses for high-quality firms because of a ripple effect along the quality ladder.

Our work relates to the literature estimating firm's product quality using trade data. Roberts, Xu, Fan, and Zhang (2017), Gervais (2015), Hottman, Redding, and Weinstein

(2016) or Piveteau and Smagghue (2018) estimate demand functions at the microeconomic level in order to disentangle price-competitiveness from non-price competitiveness in the dispersion of export performance.[4] These papers proceed by specifying a CES demand system and therefore are silent about the differential impact of trade liberalization along the quality ladder. By contrast, we are the first to estimate a random coefficient demand system using firm-level trade data. Moreover, we add to the many studies linking trade and firm quality decisions. Different channels have been documented to explain this relationship, e.g. better access to high quality inputs (Bas and Strauss-Kahn, 2015; Fieler, Eslava, and Xu, 2018); better access to destination markets with a high demand for quality (Verhoogen, 2008; Bastos, Silva, and Verhoogen, 2018). We contribute to this literature by showing that within product-destination markets, foreign competition can impact quality decisions by changing the income composition of their residual consumers. Relatedly, Medina (2017) documents that Peruvian firms switch to a different product category, of higher quality, when facing a negative shock in their core product from Chinese competition. On the contrary, we emphasize the role of unobserved vertical differentiation to explain the heterogeneous effects of competition within product categories.

This paper also contributes to a fast-growing literature on the effect of trade with low-cost countries. An important part of this literature has emphasized the adverse effects in developed economies on industries or regions exposed to Chinese import competition (Autor et al., 2013). Khandelwal (2010) shows that US industries with shorter quality ladder are more likely to suffer from a rise in low-cost country competition. Moreover, 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 et al. (2016). Ahn et al. (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. Holmes and Stevens (2014) also emphasizes the heterogeneous effect of China within industries. In their theory however, the heterogeneity is explained in terms of producing standardized versus specialized goods. Our paper differs in that we rely on a structural approach that 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 mitigate the consequences of the China shock.

Finally, our paper adds 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 consumer gains from trade. Faber and Fally (2017) and Hottman and Monarch (2017) introduce non-homothetic preferences to analyze the het-

[4] See Hallak and Schott (2011) or Feenstra and Romalis (2014) for similar studies at a more aggregated level.

erogeneous impacts across consumers of changes in product prices. Closer to our paper, Adao, Costinot, and Donaldson (2017) and Heins (2016) also follow Berry et al. (1995) when introducing mixed preferences to generate heterogeneous patterns of substitution across countries. In contrast to these papers, we use 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 low-cost competition varies along the quality ladder. Section 3 introduces the demand system and the specification used to describe the quality choice made by firms. Section 4 details the estimation of the demand system and section 5 describes the results of this estimation. Finally, we quantify the impact of Chinese competition on French firms and estimate the supply side of the model in section 6, while section 7 concludes.

2 Data and Motivating Evidence

In this section, we use French customs data at the microeconomic level to document heterogeneous patterns of substitutions across firms in international markets, contradicting the IIA assumption present in many trade models. We first document the dataset used in this paper, and then documents the heterogeneous effects of foreign competition on French firms.

2.1 Data

We employ two sources of information on international trade flows. First, we exploit individual trade data collected by the 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 and have been frequently used in the international trade literature.[5] The information is disaggregated at the firm, year, destination or origin country and eight-digit product category of the combined nomenclature (CN8).[6] The second source of trade data is the BACI database, developed by the CEPII. This 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.

We perform two tasks to harmonize the two datasets. First, we aggregate customs data at the six-digit level of the HS classification to obtain consistent product categories across datasets. Moreover, since the HS classification evolves over time, we apply the

[5] See Eaton et al. (2011) for instance.

[6] Only 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 aggregated French trade.

algorithm described in Pierce and Schott (2012) to obtain well-defined and time-invariant product categories at the six-digit level. Second, we harmonize the units used to define the quantity of these trade flows. 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 liquids is the volume in liters), rather than in kilos. By contrast, BACI only use weights as quantities, declared in tons. In order to harmonize the customs data, we follow a similar strategy used to construct BACI: we compute a conversion rate from USUP to kilos based on flows for which both weight and USUP are declared. We use this conversion rate to assign a weight to observations where only the USUP is declared. See appendix A for details on this procedure.

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. Trade values are measured free-on-board (FOB) in the currency of the exporter, such that they do not reflect final prices actually faced by consumers in the destination country. Therefore, we first convert unit values into the importer's currency. Second, we inflate them by an ad valorem transportation cost computed from the National Supply and Use Tables from 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 Statistical classification of products by activity (CPA) from 1995 to 2011.[7] 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. Therefore, we obtain import prices from several origins that reflect the final prices observed by consumers in the destination market.

Finally, because unit values in trade data are known to be noisy, we eliminate observations with extreme values. Specifically, we exclude observations for which the price is twenty times larger or lower than the average price in a destination market, or seven times larger or lower than the average price charged by that firm across destinations.[8]

Our final dataset combine bilateral export values and their unit values between 38 countries at the six-digit product level. It is augmented by firm-level trade data from French exporters into these 38 destinations. This amounts to more than 37 millions observations, almost 15 millions of them from individual French firms. In the next section, we use this dataset to document the co-movement between French exports and foreign competition.

[7]The 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.

[8]Precisely, we run regressions of log prices on destination fixed effects or firm-product-year fixed effects and eliminate observations when the residual is larger than 3 or 2 respectively, or lower than -3 or -2. See appendix A for details.

2.2 Stylized Facts

In this section, we show that the patterns of substitution between firms in foreign markets is related to vertical differentiation. More precisely, we show that French exporters are differently affected by heterogeneous sources of foreign competition, depending on their position in the price distribution.

In order to highlight these heterogeneous effects of foreign competition, we start by classifying French exporters according to their position in the price distribution. In order to do so, we estimate the average price of a firm-product-destination triplet in the first years of the sample, relative to the average price in the destination-product market. In other words, we run the following specification for all observations from French firms before 2001:[9]

$$\ln \text{price}_{fdpt} = \gamma_{fpd} + \delta_{dpt} + u_{fdpt}. \tag{1}$$

The fixed effect γ_{fpd} measures the position of the triplet fpd in the price distribution. From this measure, we label a triplet as 'low-price' if it belongs to the first quartile of the γ_{fpd} distribution and 'high-price' if it belongs to the fourth quartile. We will use this classification to compare the export trajectories of French firms in foreign markets.

As a first look into the data, we adopt a "difference-in-differences" approach and identify product categories in which the rise of low-cost competition has been the strongest. To do so we compute, for each six-digit product categories, the change in the global market share of low-cost countries between before 2001 and after 2006.[10] Based on this change in market shares, we classify a product category as control if it belongs to the lowest quartile, and as a treatment if it belongs to the highest quartile: the control group gathers product categories for which the change in market shares between pre-2001 and post-2006 is less than 2 points while products categories belonging to the treatment group has seen the market shares of low-cost countries rise by at least 29 points.

Based on this definition of our treatment and control groups, we can now investigate how the dynamics of French exporters vary with an increase in low-cost competition. In figure 1, we compare the average change in log market share from 1997 for four different groups: high and low-price French firms in treated and control product categories. The figure shows that firms with high and low prices display similar trajectories in markets that have not recorded an increase in foreign competition (control group): on average, market shares of surviving firms in both groups have decreased by 25% between 1997 and 2010. On the contrary, when looking at products where the market share of low-cost countries have greatly increased (treated group), we observe different trajectories across firms: high-price firms had similar trajectories than firms of the control group, while

[9] We use the first four years of the sample (1997-2000) to mitigate measurement errors that might arise from using only one observation for classifying firms into the price distribution.

[10] We classify as "low-cost" countries that belong to the low or middle-low income grouping from the World Bank. See table 8 in appendix A for details.

low-price firms suffered substantially more. Surviving low-price firms in the treatment group lost 50% of their market shares on average. These results suggest that French firms selling low-quality goods in foreign markets might have been disproportionally more affected by the increasing competition of firms from low-cost countries.

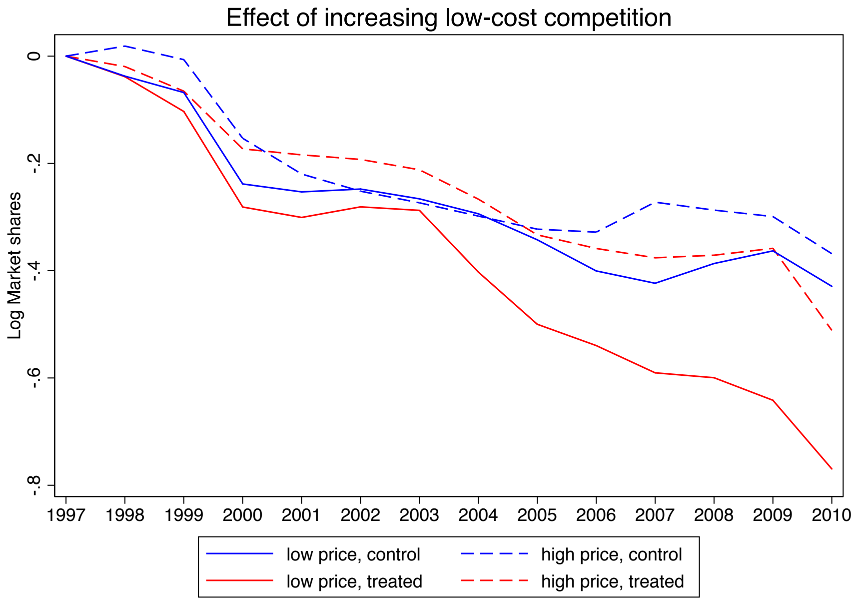

FIGURE 1: Low-cost competition impacts low-price varieties more.

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. See main text for details.*

In order to confirm the significance of these results, we look at the correlation between the export performance of different French firms in foreign markets, and the market shares of foreign countries with different levels of development. Specifically, we regress the logarithm of export values by French firms in destination markets on the penetration rate of foreign countries in these markets. Moreover, we include two types of fixed effects. First, a destination-HS6-year fixed effect such that we only measure the performance of French firms relative to each other within a market. Second, we include a firm-HS6-destination fixed effect to identify variations within the panel dimension of our data. More precisely, the regression is the following:

$$Y_{fdpt} = \sum_{q=1}^{4} \alpha_q \{PQ_{fpd} = q\} + \sum_{q=1}^{4} \delta_q \{PQ_{fpd} = q\} \times MSL_{dpt} + FE + \varepsilon_{fpdt},$$

where Y_{fdpt} will be either the logarithm of export values or a dummy for survival for firm f, product p in destination d at time t. MSL_{dpt} is the current market share of low-cost countries in each destination-product market. We interact this market share with a full set of dummies for the price quartile of the firm-product in that destination PQ_{fpd} (as defined from firm fixed effects in equation (1)). As such, δ_q measures the relative impact of low-cost competition on French firms across price levels.

TABLE 1: High-price varieties suffer less from low-cost competition

Dependent variable:	*log export*		*Survival*	
	(1)	(2)	(3)	(4)
2nd price quartile	-0.21***	.	0.0096***	.
	(0.01)		(0.0008)	
3rd price quartile	-0.31***	.	0.017***	.
	(0.01)		(0.0008)	
4th price quartile	-0.26***	.	0.00042	.
	(0.010)		(0.0008)	
Low-cost penetration				
× 2nd price quartile	0.55***	0.15***	0.033***	0.060***
	(0.04)	(0.04)	(0.004)	(0.009)
× 3rd price quartile	0.83***	0.23***	0.040***	0.091***
	(0.04)	(0.04)	(0.004)	(0.009)
× 4th price quartile	1.17***	0.19***	0.058***	0.11***
	(0.04)	(0.04)	(0.004)	(0.008)
N	5 916 958	5 784 427	5 690 561	5 570 680
R^2	0.45	0.87	0.15	0.40
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.

We report the results of these regressions in table 1.[11] 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 low-cost penetration rates. 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 low-cost countries goes up in a market, the market share of high-price firms decreases relatively less than the one of low-price firms. Even if the magnitude

[11] The estimation sample is smaller than the full dataset because our price quartiles are defined on observations before 2001. Therefore, only French varieties that were exported before 2001 are included.

of the coefficients is much more limited, and the coefficients on quartiles 2 to 4 do not differ statistically, the conclusion remains similar whether or not we include firm-product-destination fixed effects: firms from the first price quartile lose more from the increase in low-cost competition. Specifically, an increase of 10 points in the market shares of low-cost countries is associated with a 2 percent larger decrease in the market shares of low-price varieties.

In column (3) and (4) of table 1, we verify that these results extend to the extensive margin. We proceed by estimating a linear probability model where the dependent variable $Survival_{fpdt}$ is a dummy equal to one if trade flow fpd is still active in $t+1$. Results on survival confirm that the differential effect of low-cost competition also applies at the extensive margin: according to column (4), when low-cost countries gain 10 points in market shares, the survival rate of low-price firms decrease by one point relative to high-price firms.

A potential explanation for these results could be that low-price firms are less resilient to all types of competition, and not specifically to low-cost 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.[12] Results displayed in table 2 show that high-price firms tend to be slightly more affected by an increase in competition from high-cost countries. More precisely, while export values of different price categories are equally affected by a rise in the market share of high-cost countries (column 2), survival rates of high-price exporters decrease faster with high-cost competition (column 4).

Overall, these findings are consistent with the idea that the nature of foreign competition matters to explain its heterogeneous impact on French firms. Our hypothesis is that varieties that are closer in the product space, and in particular in the price distribution, display stronger substitution patterns. Figure 11 in the appendix B supports this hypothesis: it shows that prices of varieties from developing countries are closer to those of low-price French exporters.

We conclude from these results that standard models of demand, in which all varieties are equally substitutable within a product category, cannot account for the observed heterogeneity in the effects of foreign competition. In the next section, we develop an empirical model that can not only account for these patterns, but also generate realistic implications for mark-up distribution, and for the endogenous quality response of firms to competition changes.

[12] Once again, we rely on the classification from the World Bank to categorize a country as high-cost. See table 8 in appendix A for the detailed list.

Table 2: Low-price varieties suffer less from high-cost competition

Dependent variable:	*log export*		*Survival*	
	(1)	(2)	(3)	(4)
2nd price quartile	0.086***	.	0.028***	.
	(0.02)		(0.002)	
3rd price quartile	0.044	.	0.038***	.
	(0.02)		(0.002)	
4th price quartile	0.25***	.	0.040***	.
	(0.02)		(0.002)	
High-cost penetration				
× 2nd price quartile	-0.33***	-0.058	-0.021***	-0.036***
	(0.03)	(0.03)	(0.003)	(0.007)
× 3rd price quartile	-0.37***	0.014	-0.023***	-0.055***
	(0.03)	(0.03)	(0.003)	(0.007)
× 4th price quartile	-0.55***	0.030	-0.048***	-0.057***
	(0.03)	(0.03)	(0.003)	(0.006)
N	5916958	5784427	5690561	5570680
R^2	0.45	0.87	0.15	0.40
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.

3 Model

We present an empirical model of trade that features realistic substitution patterns between varieties. In particular, products that share similar characteristics, or which are close in the product space, will be stronger substitutes. This feature arises from the presence of heterogeneous consumers which differs in their preferences over product characteristics. In addition to capturing complex substitution patterns, the presence of heterogeneous consumers also generates desirable features: the model predicts variable mark-ups correlated with product quality, as well as quality adjustments in response to a changing competitive environment.

We first describe the role of heterogeneous consumers by deriving the demand function of a firm. We then move to the supply side, describing the cost function of the firm and in particular the cost of producing high quality products. Finally, we study the optimal pricing and quality choice made by firms.

3.1 Demand Side

The global economy is a collection of destinations d, populated with a continuum of heterogeneous consumers. In each destination, each consumer i chooses among the set of foreign varieties available, denoted Ω_d, and the domestic variety of the good. A variety is produced by a unique firm but firms 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 and γ_f is a utility shifter that is specific to firm f, which produces variety j. Moreover, ξ_{jdt} captures deviations in consumers' valuation of goods supplied by firm f across varieties and destinations. Therefore, we define $\lambda_{jdt} \equiv \gamma_f + \xi_{jdt}$, as the quality of a variety j on destination d such that λ_{jdt} contains any unobservable characteristic that raises the valuation of variety j from the point of view of all consumers in destination d. Finally, ε_{ijt} is an idiosyncratic shock in consumer i's valuation of variety j. In this utility function, α_i drives the relative importance of quality and quantity in a consumer's preferences. In the extreme case where $\alpha \to +\infty$, only quantity matters. On the contrary, when $\alpha \to -\infty$, quantity becomes a negligible part of utility and the consumer only cares about quality.

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. We assume that $e(y_i)$ is proportional to y_i, which implicitly amounts to assuming that consumers have Cobb-Douglas preferences across product categories. Therefore, the indirect utility associated to any variety j is

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

Consumers pick the variety that maximizes their indirect utility. Since indirect utilities are only defined up to a constant, we normalize the quality of the outside good - $\gamma_0 + \xi_{0t}$ - to zero. Consequently, the measured quality of foreign varieties should be interpreted in deviation to the quality of the outside good. In the empirical application, we will consider the domestic variety as outside good.[13] Nevertheless, we do not set the price of the outside good to zero: such normalization would impose strong assumptions on the substitution patterns between the outside good and other varieties. In the estimation, we therefore account for the price of the domestic good.

Assuming that the idiosyncratic shock ε_{ijt} follows a Type I extreme-value distribu-

[13]See Khandelwal (2010) for a similar assumption.

tion, the probability that consumer i in destination d buys variety j is

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

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}), from the ones that are consumer-specific (μ_{ijdt}).

From individual to aggregate demand Having described the individual decision made by consumers, we can now obtain the aggregate demand received by a firm in each destination. Since consumers are heterogeneous in their preferences, and therefore decisions, we obtain the aggregate demand by integrating these individual decisions over the consumer's distribution. Specifically, we assume these preferences are distributed as follows

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi y_i + \Sigma \nu_i, \qquad y_i \sim F_{y,d}(y),\ \nu_i \sim F_\nu(\nu) \tag{2}$$

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 (2) implies that the random coefficients depend linearly on the log-income of the consumer y_i and a vector of random shocks ν_i. Importantly, the distribution of y_i, $F_{y,d}$, will depend on the demographic characteristics of each destination market d.[14] We do not constrain the sign of the relationship between α_i and y_i, even though we expect this relationship to be negative as richer consumers are likely to value quality more.

Equation (2) implies that 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 to consume a variety j as a function of her log-income y and her preference shock ν

$$\mathbb{P}_{jdt}(y,\nu) = \frac{\exp\left(\delta_{jdt} + \mu_{jdt}(y,\nu)\right)}{1 + \sum_{j\in\Omega_d} \exp\left(\delta_{jdt} + \mu_{jdt}(y,\nu)\right)}. \tag{3}$$

It follows that the sales of variety j in destination d are

$$r_{jdt} = \int e(y(\nu)) \frac{\exp\left(\delta_{jdt} + \mu_{jtd}(y,\nu)\right)}{1 + \sum_{j\in\Omega_d} \exp\left(\delta_{jdt} + \mu_{jdt}(y,\nu)\right)} F_{y,d}(y) F_\nu(\nu) dy\, d\nu \tag{4}$$

and the respective market share (in revenue) is

$$s_{jdt} \equiv \frac{r_{jdt}}{\sum_{j\in\Omega_d} r_{jdt}} = \int \mathbb{P}_{jdt}(y,\nu)\, \omega_d^{(1)}(y,\nu) dy\, d\nu\,, \tag{5}$$

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

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

3.2 Supply Side

Having described the demand side, we can now turn to the cost function of firms. This supply side will not be directly used in the main estimation, but will be important when quantifying the quality adjustments in our counterfactual exercise.

We assume that firms have constant marginal costs of production. These marginal costs depend on product characteristics and product quality. Specifically, the logarithm of the marginal cost is

$$\ln c_{jdt}(\lambda) = h(\lambda) + x_{jt}\rho + \eta_{jdt}\lambda + \varphi_{jdt}. \tag{6}$$

Product characteristics affect production costs through the vector of parameters ρ. Moreover, we assume that quality enters the marginal cost function through a flexible polynomial $h()$, and an idiosyncratic quality-elasticity of costs η_{jdt}.[15] As such, firms are heterogeneous along two dimensions: the quality-elasticity of their marginal costs, η_{jdt}, and their productivity φ_{jdt}. We do not impose assumptions on these measures of heterogeneity: they will be recovered from the data, by matching both the observed price and the estimated quality measure.

3.3 Pricing and quality decisions

Having described the supply and demand fundamentals, we can now turn to firm optimal decisions. Notice that we don't need to assume that firm decisions are optimal in the data when we estimate the demand side of the model (section 4). It is only after estimating the demand side that optimal pricing and quality will matter, when we recover marginal production costs from observed prices, and when we quantify the quality response of French exporters in our counterfactual experiment.

Assuming constant marginal cost of production, the profit function is

$$\pi_{jdt}(p,\lambda) = r_{jdt}(p,\lambda)\left(1 - \frac{c_{jdt}(\lambda)}{p}\right), \tag{7}$$

which emphasizes the two choice variables for a firm in each destination: their price and their product quality. We assume that both decisions are made simultaneously by

[15] We assume that the cost of quality only appears through the marginal costs of the firm. Alternatively, we could have introduced fixed costs or adjustment costs to explain why firms choose a finite quality level. We make this decision because we are able to estimate the impact of quality on measured marginal costs. On the contrary, identifying fixed costs is more challenging given our observables. Moreover, since we find in our counterfactual that quality plays a limited role in mitigating the impact of low-cost competition, the existence of frictions when adjusting quality, in addition to the effect on marginal costs, would only reinforce our results.

solving both first order conditions on profit.[16]

Optimal pricing Firm optimal pricing rule is

$$\frac{p_{jdt}}{c_{jdt}} = 1 + \frac{1}{\int (1 - \mathbb{P}_{jdt}(y,\nu)) \exp(\alpha(y,\nu))\, \omega^{(2)}_{jdt}(y,\nu)\, dyd\nu}, \tag{8}$$

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

Intuitively, the mark-up charged by a firm is a function of the price elasticity of the average consumer it serves. Therefore, firms producing goods that are more appealing to rich consumers set higher mark-ups since their average consumer is less price-sensitive. This result highlights a desirable feature of a model with random coefficients: mark-ups charged by a firm is increasing with the quality of its products. While most trade models explain the correlation between prices and quality by the cost of quality, our framework can explain price dispersion from mark-ups variations. Moreover, we can see that in the absence of heterogeneity across consumers, we obtain the usual pricing rule from oligopolistic competition: $\frac{p_{jdt}}{c_{jdt}} = 1 + \frac{1}{(1-\mathbb{P}_{jdt})\exp(\alpha)}$. In this context, mark-ups decrease with the price elasticity of the representative consumer and increase with the market share of the firm.

Optimal Quality Higher quality leads to an increase in the sales of a firm, conditional on prices. At the same time, quality also increases the marginal cost of production, which leads to higher prices and lower sales. Therefore, when choosing their optimal quality, firms trade-off between supplying an appealing product and an affordable product. The outcome of this trade-off directly depends on consumers' price-elasticity: price-elastic consumers are less willing to pay higher prices to purchase higher quality goods.

We formalize this intuition by deriving the first order condition of quality in equation (9). 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. On the other hand, 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 quality-elasticity of marginal costs and on a weighted average price-elasticity of the firm's consumers.

$$\int (1 - \mathbb{P}_{jdt}(y,\nu))\omega^{(2)}_{jdt}(y,\nu)dy\, d\nu = \frac{\partial \ln c}{\partial \lambda} \int \exp(\alpha(y,\nu))(1 - \mathbb{P}_{jdt})\omega^{(2)}_{jdt}(y,\nu)dy\, d\nu \tag{9}$$

This first order condition can be rewritten as follows to highlight the link between the

[16] We assume that all firms behave as single-product firms. Even though firms produce different varieties of shoes, the market shares of French firms is very small in foreign markets. Therefore, we do not expect cannibalization effects to matter in pricing and quality decisions and assume single-product firms for computational convenience.

quality-elasticity of costs and the price-elasticity of their consumers.

$$\frac{\partial \ln c}{\partial \lambda} = \frac{1}{\int \exp(\alpha(y,\nu))\, \omega^{(3)}_{jdt}(y,\nu) dy\, d\nu} \tag{10}$$

with $\omega^{(3)}_{jdt}(y,\nu) \equiv \frac{e(y)(1-\mathbb{P}_{jdt}(y,\nu))\mathbb{P}_{jdt}(y,\nu)F_{y,d}(y)F_\nu(\nu)dyd\nu}{\int e(y)(1-\mathbb{P}_{jdt}(y,\nu))\mathbb{P}_{jdt}(y,\nu)F_{y,d}(y)F_\nu(\nu)dyd\nu}$. Therefore, the lower the price-elasticity of their consumer, the more firms are willing to increase their cost through quality upgrading. Importantly, this first-order condition only defined the optimal quality if the marginal cost function is increasing and convex with quality, ensuring that the second-order condition is satisfied. We will verify that this condition is satisfied when estimating the shape of the cost function.

Condition (10) implies that firms with richer consumers, who are less price-elastic, will choose a higher quality for their products. Moreover, when the competitive environment changes, consumers will adjust their purchasing decisions, potentially moving the average price-elasticity faced by firms. For instance, if the rise of low-cost competition causes French firms to lose consumers that are very price-elastic, the average price-elasticity faced by French firms will decrease. As a consequence, it will be optimal for French firms to upgrade their quality to reflect the preferences of a richer set of consumers. As such, foreign competition can trigger quality adjustments by firms. It is crucial to note that this mechanism would not be at play in the absence of heterogeneity across consumers. In the special case of homogeneous consumers, low-cost competition would not change the composition of firm sales across consumer and would thus leave 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 explaining the preparation of the data and the choice of the footwear industry to perform the estimation. Then, we discuss the econometric specification and our strategies to deal with the endogeneity of prices and the presence of zeros in trade data. Finally, we describe the algorithm to compute the estimator.

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 category 64: 'Footwear; Gaiters and the like; parts of such articles'. These eight positions exclude sport shoes, such as soccer shoes or ski boots, waterproof shoes and shoe parts.[17]

We pick the footwear industry mainly for two reasons. First, shoes are a well-defined

[17] The list of the included and excluded product codes is reported in table 9 in appendix A.

consumer good. This allows us to obtain prices that are consistent across varieties, and product characteristics that can be inferred from the data. In particular, we create four product characteristics from the description of the product codes, that will be used 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 A provides details regarding this information.

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 throughout 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 ladder, similarly to other French industries. Figure 2 provides evidence of these patterns. As the market share of Chinese producers rose, the market share of cheap French shoes dropped. In the meantime, high-price French shoes were able to maintain, and even slightly gain market shares.[18]

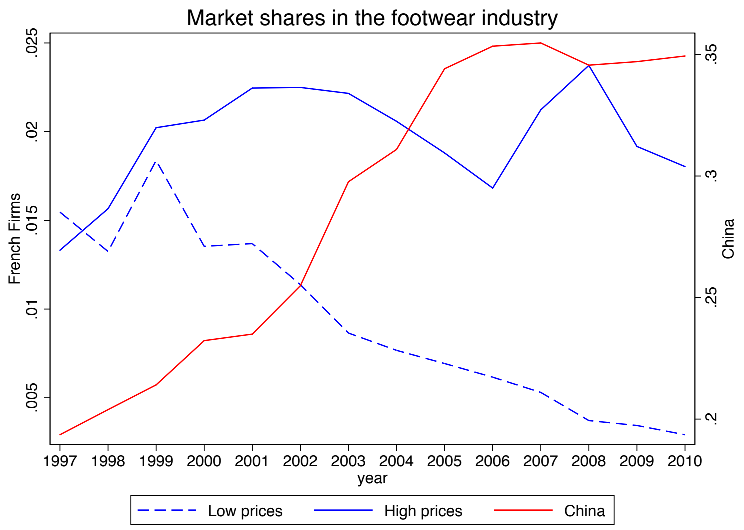

FIGURE 2: Chinese competition Hits Cheap Shoes Harder

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.

To portray a more comprehensive picture of the global changes at play in the footwear industry, we look at changes in the distribution of prices. In figure 3, we report for each year from 1997 to 2010, the distribution of French and low-cost country prices, weighted

[18]In appendix B, figure 12 describes the evolution in logarithm of market shares to be fully consistent with the figure 1 displayed in the previous section.

by their market shares. This figure shows that, as the market share of low-cost countries increases, the price distribution of French shoes diverges upward from low-cost producers. This movement suggests that market shares have been reallocated from low-price to high-price producers, either from a reallocation across firms, or from increases in the prices charged by French shoes. Both of these mechanisms suggest heterogeneous impacts of low-cost competition along the price dimension.

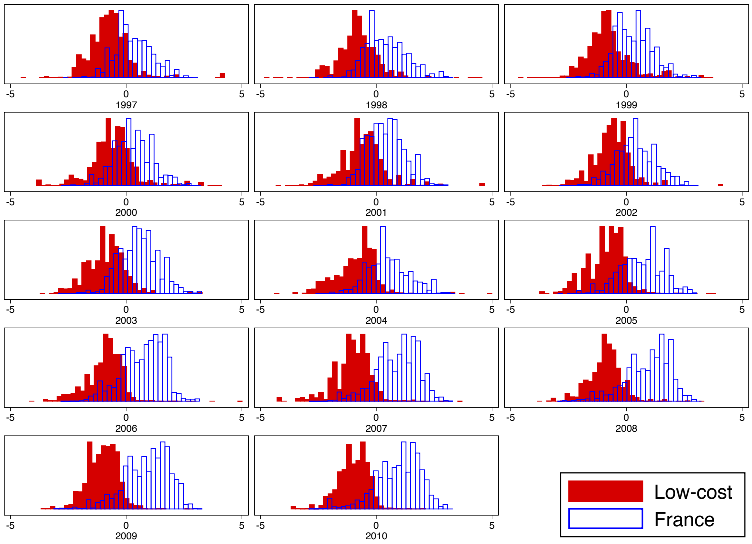

FIGURE 3: The price of French shoes diverge from low-cost competition

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

Data cleaning Before taking the model to the data, we perform a number of operations to avoid the presence of anomalous observations in the estimation sample. We follow the same procedure used in the previous section, only this time on the subsample of footwear exports: we eliminate markets with a small number of producers, drop observations from French firms that display extreme variations, and correct extreme prices from other countries' exports.[19] This cleaning procedure leaves us with 192 425 observations during the sample period, out of which 102 127 are French. In table 3, we report summary statistics for the 2 389 French firms that are part of the sample. We notice that the median firm has only ten observations. This sparsity is typical of trade data. Moreover, we see a large dispersion in the price of one kilogram of shoes, ranging from 9 Euros at the 5th percentile to 260 Euros at the 95th percentile. Finally, the market shares of French firms are small in foreign markets. The average French firm has a market share of 0.005%, while the largest market share in the sample for a French firm is 1.6%.

[19]These different steps are described in A.

TABLE 3: Summary statistics for French firms

	Mean	*p5*	*p25*	*p50*	*p75*	*p95*
By firm:						
# observations	42.7	2	3	10	33	179
# destinations	5.9	1	2	3	7	20
# products	2.7	1	1	2	4	7
Price	75.1	8.8	21.0	40.3	83.3	263.6
Market share (%)	0.005	$2.7e^{-6}$	0.00004	.0003	.002	.02

Notes: FOB Prices in Euros. Sample of 2389 firms.

In order to implement the estimation, we also need to know the market share and price of the outside good in each market. In our context, the domestic variety is the most natural outside good available.[20] We construct its market share from the WIOD database as the share of domestic consumption in total consumption. This information is available for every year and destination country, but 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 2-digit category 'Leather, Leather and Footwear'. Moreover, the estimation requires to know the price of the outside good. For this purpose, we proxy the local price of the domestic good in a country from the price of its exports, as measured in the BACI dataset. Specifically, we regress the FOB export price of each country c, on a set of fixed effects as follows:

$$\log p_{cdpt} = \gamma_{cp}^{(1)} + \gamma_{ct}^{(2)} + \gamma_{pt}^{(3)} + \gamma_{dt}^{(4)}$$

and we construct the domestic prices from the sum of the three fixed effects $\hat{\gamma}^{(1)}$, $\hat{\gamma}^{(2)}$ and $\hat{\gamma}^{(3)}$, to obtain the price of the outside good at the product-country-year level.

4.2 Model specification

We now 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 restrict this heterogeneity to the price coefficient α_i and the preference for French goods

[20] See Khandelwal (2010) for a similar assumption in a similar context.

β_i^F. Specifically, we introduce three different sources of heterogeneity between consumers: First, we allow consumers' preferences to vary with their income, y_i. Second, we introduce two random shocks, $(\nu_i^{(1)}, \nu_i^{(2)})$ that will introduce additional variation in consumers' price-elasticity and the preference for French products. Formally, equation (2) from the previous section becomes

$$\begin{pmatrix} \alpha_i \\ \beta_i^F \end{pmatrix} = \begin{pmatrix} \alpha \\ 0 \end{pmatrix} + \begin{pmatrix} \Pi_\alpha \\ \Pi_F \end{pmatrix} y_i + \begin{pmatrix} \Sigma_\alpha & \Sigma_{\alpha,F} \\ \Sigma_{F,\alpha} & \Sigma_F \end{pmatrix} \begin{pmatrix} \nu_i^{(1)} \\ \nu_i^{(2)} \end{pmatrix} \tag{11}$$

where the shocks ν are independently and normally distributed, and y_i follows a normal distribution parametrized by the mean and standard deviations of the logarithm of the income distribution in destination d.[21]

To summarize the specification, the demand system is parameterized by seven 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 five parameters that enter linearly in the estimation of the demand system. Four of these parameters captures the average 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 self-selection of countries and firms into foreign markets. A substantial 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.

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 and a set of destination-year fixed effects. Moreover, to account for producer-specific fixed effects, we follow the method by Mundlak (1978) and add the producer-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 from this selection equation 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 these differences.

[21] As a consequence, the distribution of income, and of shocks y_i, is destination-specific.

Instruments The estimation of any demand system requires instrumental variables for prices. These variables need to be correlated with the prices charged by firms but uncorrelated with the structural error of the model which captures the unobserved determinants of 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 advantage of prices set in other markets to provide exogenous shifts in prices due to correlation in costs across markets.

We believe the use of international trade data provides a good set of instruments through the existence of exchange rates between countries. These exchange rates 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 shoe producers, which constitute the structural error of the model. Therefore, we follow the approach used in the literature aiming at estimating demand with trade data and use exchange rates as instruments for prices.[22]

However, the use of exchange rates as instruments is not sufficient to estimate the model. 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 firm imports. We construct an import-weighted exchange rate that measures movements in exchange rates faced by French firms on their imports. 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.[23] Formally, this instrument is defined as

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

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 use the import shares from the year a firm starts exporting in the data.

Moreover, 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 the ratio of total import expenditures and total export revenue, in order to cap-

[22]See Khandelwal (2010) or Hallak and Schott (2011) for instance.
[23]See Piveteau and Smagghue (2018) for further discussion on these instruments.

ture 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 generate prices adjustments while being plausibly unrelated with demand shocks or endogenous quality decisions made by 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 $Z = [z_1, ..., z_L]$ such that

$$E\left[z_l\, \varepsilon(\theta_0)\right] = 0, \qquad \text{for} \quad l = 1, .., L \tag{12}$$

where θ_0 is the true value of the parameter. Following BLP, we use the structural error of the model ξ_{fjd} to construct the error term in these orthogonality conditions. From equation (5), 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 vector 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 vector $\delta^{(h)}$, we compute $s(\delta^h, x, \ln p; \theta)$ and set

$$\delta^{(h+1)} = \delta^{(h)} + \log S - \log s(\delta^{(h)}, x, \ln p; \theta). \tag{13}$$

We iterate until the minimum of the vector of squared difference between $\delta^{(h+1)}$ and $\delta^{(h)}$ is less than 10^{-12}.[24] Moreover, we use Halton sequences to numerically approximate the integrals in the computation of $s(\delta^{(h)}, x, \ln p; \theta)$.

We denote the resulting vector of mean utilities $\delta(S, x, \ln p; \theta)$ 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, which gives us an estimate of the remaining five parameters that appear in the utility function. Finally, we obtain the structural errors of the model from

$$\hat{\xi} = \delta(S, x, \ln p; \theta) - \hat{\beta} x - \hat{\gamma} \tag{14}$$

[24] The convergence of the contraction mapping is accelerated using the Squarem acceleration method developed in Varadhan and Roland (2004), and programmed in Matlab by Chris Conlon.

We 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. 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: the only parameters that enter the GMM problem are the ones related to the distribution of the random coefficient. The other parameters (those entering the mean utility level) can be directly obtained by instrumental variables regression, hence reducing the dimensionality of the search algorithm.[25]

We obtain our GMM estimates $\hat{\theta}$ by minimizing the weighted distance of the moments created from our sets of instruments Z and the structural errors of the model $\varepsilon(\theta)$. Formally, we have

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

where Φ is a weighting matrix. 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. In both steps, we minimize the GMM objective function using a standard optimizer to which we provide the gradient of the problem. This minimization behaves well and the results appear robust to different starting conditions.

Finally, we obtain standard errors for our estimator using the GMM standard errors from Newey and McFadden (1994). Specifically, the estimated variance of our estimator is

$$\hat{V}(\hat{\theta}) = (G'\hat{\Phi}G)^{-1} G'\hat{\Phi}Z'\varepsilon(\hat{\theta})\varepsilon(\hat{\theta})'Z\Phi G(G'\hat{\Phi}G)^{-1}$$

where $\hat{\Phi}$ is the optimal weighting matrix estimated in the first stage, and G is the gradient of the objective function. However, these standard errors do not take into account the inclusion of the inverse Mills ratio in the estimation. Because this variable is generated separately from a probit model, it is necessary to take into account its estimation errors. Therefore, we also report standard errors from a bootstrap procedure. Specifically, we create 50 bootstrap samples by drawing destination$\times$year blocks of observations. For each sample, we run the selection equation to construct the Mills ratio and the GMM procedure. This procedure allows us to obtain standard errors that account for the estimation of the selection equation in the first stage.

5 Demand estimation results

In this section, we first describe the main estimation results from the GMM procedure. We then discuss several outcomes of the model to showcase how the demand system captures heterogeneity across firms.

[25] By contrast, trying to directly minimize the distance between the predicted and actual market shares would require to iterate over all the parameters, both linear and non-linear, including the large set of producer fixed effects.

5.1 Estimation results

The first step of the estimation aims to construct the inverse Mills ratio that accounts for endogenous selection. We estimate two probit models: one for the aggregate data at the country-product level and one at the firm-product level. In each model, we explain export participation by the set of instruments that is used in the GMM estimation.

Table 4: Selection equation

	Export participation	
	Countries	Firms
RER_{odt}	-0.068^{***}	-0.19^{***}
	(0.01)	(0.01)
$\overline{RER}_{ft}$		-0.059
		(0.07)
$\overline{RER}_{ft-1}$		-0.57^{***}
		(0.07)
$\overline{RER}_{ft} \times \frac{\text{imp}_f}{\text{exp}_f}$		-0.026
		(0.03)
$\overline{RER}_{ft-1} \times \frac{\text{imp}_f}{\text{exp}_f}$		-0.078^{**}
		(0.03)
N	157 472	3 487 260
R^2		

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 displayed in table 4 are consistent with our priors regarding the impact of exchange rates on export participation: for both firms and countries, 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. This is particularly true from cost shocks received in the previous year, since only lagged instruments have a significant impact on export participation. As expected, firms with a larger import ratio tend to be more affected by these cost shocks from imported inputs. From this participation equation, 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.

TABLE 5: Linear estimation results

	Dependent variable: normalized log market share			
	OLS		**2SLS**	
log price	0.24***	0.23***	-0.96*	-2.12***
	(0.06)	(0.05)	(0.5)	(0.4)
log price × inc_d	0.40***	0.43***	0.83**	1.16***
	(0.06)	(0.06)	(0.4)	(0.4)
Leather sole	-1.04***	-1.12***	-1.08***	-1.33***
	(0.1)	(0.10)	(0.1)	(0.1)
Leather top	1.17***	1.23***	1.05***	1.12***
	(0.1)	(0.1)	(0.1)	(0.1)
Fabric top	-0.048	-0.031	-0.039	0.022
	(0.08)	(0.08)	(0.09)	(0.10)
Boot	-0.57***	-0.60***	-0.58***	-0.66***
	(0.06)	(0.05)	(0.06)	(0.06)
Mills ratio		0.41*		1.16***
		(0.2)		(0.2)
R^2	0.55	0.55		
First stage F-stat			17.7	9.28
J-test p-value			0.44	0.27

Notes: Number of observations: 192 421. Standard errors between parentheses clustered at the producer level. All specifications include producer (firm or country) fixed effects. Instruments include the exchange rates between destination and origin and the four firm-specific instruments based on import-weighted exchange rates. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

We now turn to the results of the demand system estimation. Before describing the result of the GMM estimation with random coefficients, we first report results of a standard linear demand equation. This equation corresponds to the structural demand in the absence of within-country consumer heterogeneity. In this case, we regress the normalized logarithm of the market share $\log s_{fdpt} - \log s_{0pdt}$ on prices, prices interacted with the average income in the destination market, and product characteristics. Table 5 reports those results with OLS and 2SLS, to assess the performance of our instrumentation strategy.

Results in table 5 validate our empirical strategy. First, the instruments address the traditional endogeneity concerns related to the estimation of demand equation. In the absence of instruments (columns 1 and 2), we estimate a positive coefficient on prices. On the contrary, the 2SLS specifications (columns 3 and 4) present a negative coefficient on price, as expected in a demand equation. Second, we do find that richer countries tend to have consumers with a lower price elasticity.[26] This is reassuring regarding the variation we hope to capture with our random coefficients. Finally, the Mills ratio has a positive

[26] The income in the destination is normalized such that the average country has an income of 0.

and significant coefficient, which demonstrates the importance of endogenous selection in foreign markets. Moreover, we find a much larger price elasticity when including the price ratio, which shows that this selection effect generates an important attenuation bias on the structural parameters.

We now turn to the specifications with random coefficients. Table 6 reports the results from different specifications: in columns (1) and (2), we only allow income to drive consumers' preferences, while columns (3) and (4) present the full specifications with the additional random shocks ν_i (see equation (11)). Given the model specification, the price-elasticity of demand for the average consumer is equal to $-\exp(\alpha)$. Therefore, column (4) implies an demand elasticity at the average of -2.36, consistent with the results obtained in the absence of random coefficients. Moreover, the results show that richer consumers have a smaller price elasticity, since the parameter Π_α is negative. However, we do not find a significant effect of income on the relative preferences for French good (parameter Π_F). Similarly, the model does not identify additional heterogeneity in preferences besides the ones captured by income. In particular, the effect from the additional shocks ν_i are very imprecisely estimated, which suggest that there is little heterogeneity left once controlling for variations in income.

TABLE 6: Random-coefficients estimation results

	(1)	(2)	(3)	(4)	
α	0.22**	0.77***	0.45	0.86*	
	(0.11)	(0.07)	(1.6)	(0.50)	[0.36]
Π_α	-0.51***	-0.38***	-0.50	-0.38*	
	(0.06)	(0.04)	(1.0)	(0.22)	[0.10]
Π_F	-0.12*	0.13	-0.11	0.19	
	(0.07)	(0.08)	(0.81)	(0.30)	[0.41]
Σ_α			0.05	0.07	
			(1.4)	(1.4)	[0.06]
Σ_F			0.67	1.14	
			(65)	(18.3)	[1.0]
$\Sigma_{\alpha,F}$			-0.005	-0.05	
			(4.3)	(1.5)	[0.07]
$\Sigma_{F,\alpha}$			-0.84	-0.82	
			(42)	(9.5)	[0.97]
Mills ratio		0.98***		0.84***	
		(0.04)		(0.2)	[0.53]

Notes: Number of observations: 192 421. All specifications include producer (firm or country) fixed effects and product characteristics (not reported). Robust standard errors between parentheses. Standard errors from 50 bootstrap samples between brackets. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Regarding other variables, the coefficient on the Mills ratio is significant and positive, which confirms the importance of endogenous selection in explaining export participation. Moreover, when comparing columns (3) and (4), the price-elasticity goes from -1.56 to -2.36 after accounting for this selection. This is another confirmation of the importance of the bias due to endogenous selection. Finally, bootstrapped standard errors suggest more precisely estimated parameters. While this is surprising since these bootstrap estimates account for the estimation errors from the selection equation, this discrepancy can be explained by different assumptions made on the data generating process: when implementing the bootstrap, a natural sampling procedure is to draw blocks of market×year observations rather than individual observations, which imposes clustered standard errors. However, the robust standard errors obtained from the GMM estimation does not impose parametric forms for the covariance matrix of the error term, which could explain larger estimates.[27]

5.2 Estimation outcomes

We now describe the distribution of mark-ups, price elasticities and cross-elasticities with Chinese exports, among French firms. These distributions highlight the role of consumer heterogeneity in the dispersion of market power and exposure to Chinese competition.

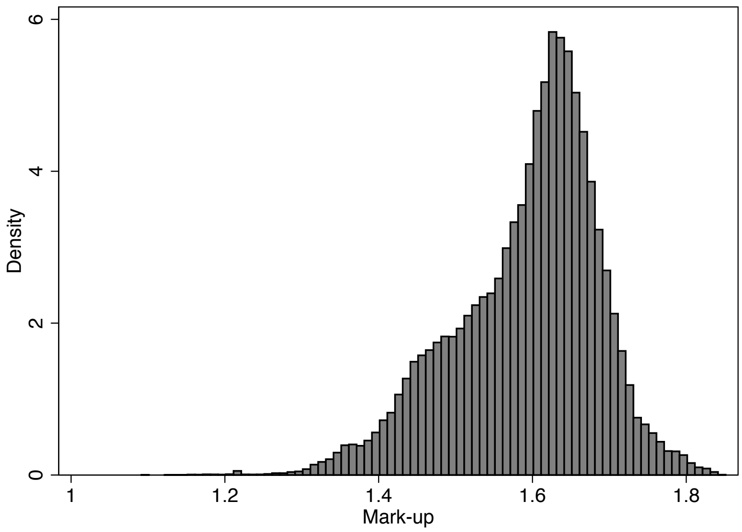

FIGURE 4: Distribution of mark-ups of French firms

Figure 4 displays the distribution of mark-ups for French firms in all different markets they export to. Therefore, the unit of observation is a specific variety in a foreign market

[27]An alternative sampling procedure would be to draw producers rather than markets. However, in our context where both countries and firms are producers, it would not be reasonable to draw firms and countries with the same probability. We implemented a bootstrap procedure where only firms were drawn and not countries, and this sampling method led to smaller standard errors.

at a given time. These mark-ups are directly computed from equation (8) using the parameter estimates. The average mark-up is around 60% which is at the higher end of estimates found in the literature, but could be due to the fact that French shoes are high-end varieties on average. Interestingly, we see a large variation in these mark-ups: some products only have a 30% mark-up, while others are closer to 80%.

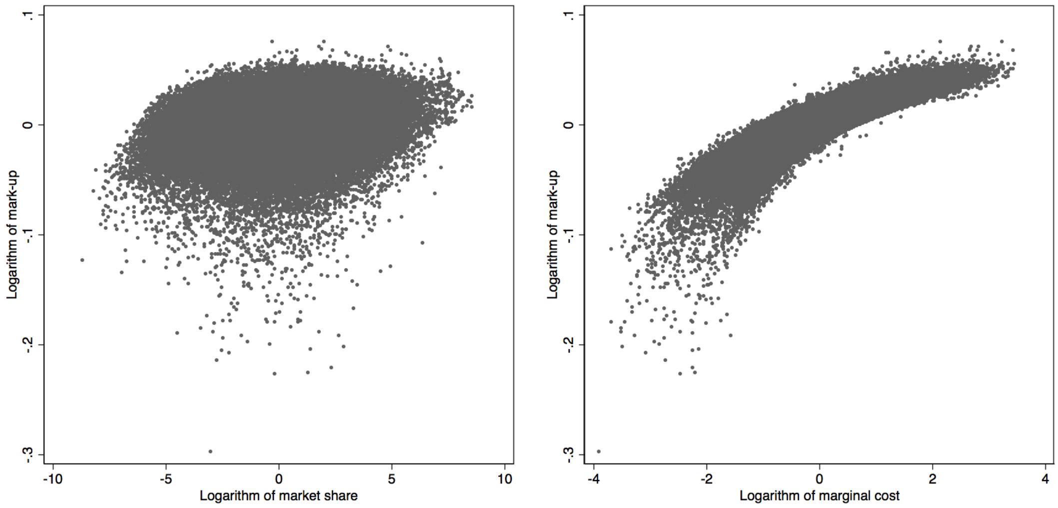

FIGURE 5: Correlation of mark-up with market share and marginal cost

Notes: All three measures have been normalized within product-destination-year group.

In order to understand this dispersion across firms, figure 5 plots the relationship between mark-ups and market share (left panel), and between mark-ups and marginal cost of production (right panel). This figure shows that most 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. This prediction is a direct consequence of the introduction of random-coefficients: 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. However, we do not find a significant effect of market shares on mark-ups: since we are looking at exporting firms to foreign markets, all firms have very small market shares which do not lead them to any oligopolistic pricing behavior.

Finally, this heterogeneity is also reflected by the dispersion in price-elasticities faced by French firms. In figure 6, we plot the distribution of own price-elasticity among French firms (left panel), and their cross-elasticity with Chinese exports (right panel). The own 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

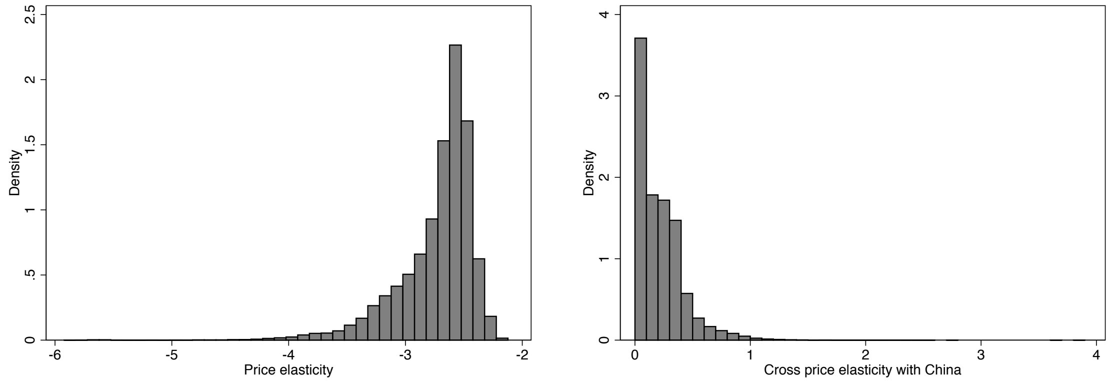

FIGURE 6: Distribution of own and cross-price elasticities (French firms).

can see from the figure a large dispersion in price-elasticity, ranging from 2.5 to 4. This dispersion similarly reflects the fact that firms face very different average consumers, affecting their optimal response in terms of prices. Moreover, serving different consumers also implies that firms are unequally affected by low-cost competition. For instance, when Chinese competition increases, firms with low prices are specifically selling to consumers who are likely to turn to Chinese producers, given their preference for low-price products. The right panel of figure 6 shows that French firms are very differently affected by a change in Chinese firms' prices. A large share of French firms are barely affected by such a change, while 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 more profitable for these firms 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 7 that reports the relative average quality of French exporters over time, depending on their position in the price distribution in 1997.[28] We can see that firms with low prices in 1997 (and low quality), have been bridging some of the quality gap to the upper quartile. This result is consistent with the model prediction that the rise of low-cost competition should induce quality upgrading from firms at the bottom of the price distribution.[29]

[28]In order to build this graph, we first bin French exporters into price quartiles in 1997. Then, we compute the average quality across all destination markets, for each quartile-year group. Finally, we normalize the average quality of the top quartile is zero over the period.

[29]Note that the quality estimates used in figure 7 are obtained from estimating the demand side of the model only. In that sense, this figure was not obtained by imposing that firms behave optimally and

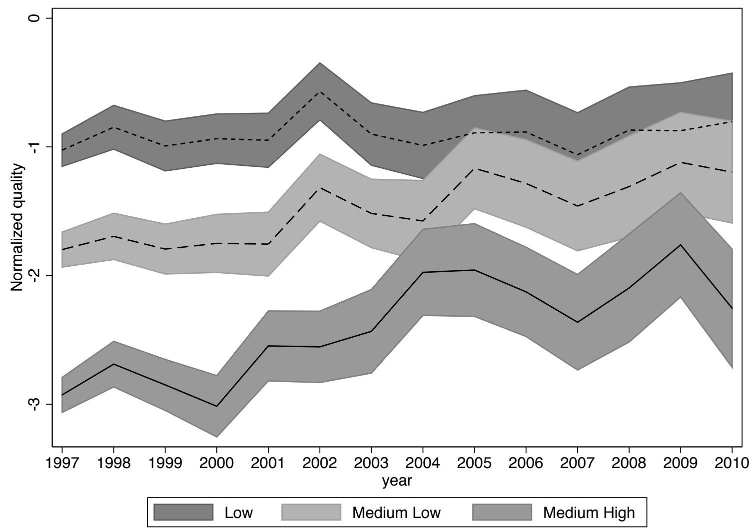

FIGURE 7: Low Price Varieties Upgrade their Quality over the Period

Notes: The figure reports the yearly average quality of French firms belonging to different price quartiles in 1997: Low, Medium low and Medium High. Average qualities are normalized such that the average quality of the High price quartile is equal to zero. Shaded area describes the 95% confidence interval of each group's average.

This convergence of quality across French firms is concurrent with the documented increase in low-cost competition in the footwear industry. However, even though this result is suggestive of some relationship between competition and quality adjustment, many other factors could explain this correlation: changes in technology, input prices or preferences could all be reasons that lead French firms to upgrade the quality of their product. Therefore, in order to isolate and quantify the role of low-cost competition in triggering this mechanism, we use our model to perform a counterfactual experiment: what would have happened if China did not grow during the last 15 years? In particular, we investigate how heterogeneous the China shock is across French firms, and to which extent French firms adjusted to this shock through quality upgrading.

6 Quantifying the unequal impact of the China shock

Having estimated a model of demand for the shoe industry, we can make predictions about how shoe producers would have performed in a different environment. In particular, we investigate the rise of China in the footwear market, and its consequences on French producers. We are most interested in two elements. First, how heterogeneous is the effect of this shock along the price ladder. Second, to which extent has quality upgrading shielded French firms from the China shock. We start by describing the counterfactual experiment and present the results in a simple case where French firms

upgrade their quality in response to Chinese competition.

cannot change the quality of their products. Then, we move to a scenario where firms are allowed to adjust their quality: we describe how we discipline this response, and show this additional margin of adjustment changes the results.

6.1 Experiment without quality adjustment

The demand system estimated in the previous section relies on two sets of fundamentals: the distribution of consumer preferences and the characteristics of producers (price and quality). To study the impact of the China shock, we run our model assuming that the fundamentals of Chinese producers have not changed during the time period. Specifically, for each Chinese variety in each destination market, we compute the average price and quality from 1997 to 2000. We then assume that these prices and quality measures have stayed the same from 1997 to 2010, and simulate the model under this new set of fundamentals.

Even though French firms cannot adjust the quality of their product, we allow them to update their pricing strategy. In a scenario where China does not grow, we expect French firms to have a different pricing strategy since they would serve a different set of consumers. Therefore, we keep marginal costs to their estimated value, but recompute the optimal mark-up charged by French firms. Practically, we find counterfactual prices and market shares iterating until convergence between equation (8) (defining optimal mark-ups) and (5) (defining market shares). Throughout this procedure, we assume that other foreign countries maintain their actual prices in this alternative scenario.[30]

We present the results of this counterfactual experiment in figure 8. Specifically, we compare the market shares, profit and mark-ups in the presence of the China shock in 2010, relative to the scenario in which prices and quality of Chinese producers have stayed at their levels from before 2001. For each destination market, we divide the sample of French firms based on their position in the local price distribution. Then, for each decile, we report the median change across all firms and destinations in the logarithm of market shares, mark-ups and profits.[31] Figure 8 shows the unequal effect of the China shock. Firms at the bottom of the price distribution see their market shares decrease by 20%. On the contrary, firms at the bottom of the price distribution only experience a 12% reduction in their market share. Therefore, even though all firms lose from Chinese competition, low-price firms lose disproportionately. This decrease in market shares is directly translated into lower profits, in similar proportions to market share losses. Finally, we can see that French firms tend to increase their prices in response to this competition: since Chinese producers serve price-elastic consumers, the average

[30] We do not allow foreign countries to adjust their mark-ups since this would require to use the model to back out country-level mark-ups. Because our framework considers a foreign country as a single producer, and countries have very large market shares compared to firms, this operation would lead to infer very large country-level mark-ups. As a result, we decide to maintain prices and qualities of non-French varieties as estimated from the data.

[31] We use the median effect because we see a broad dispersion across products and destinations. Figure 13 in appendix B provides the distribution of these effects for the logarithm of the market share.

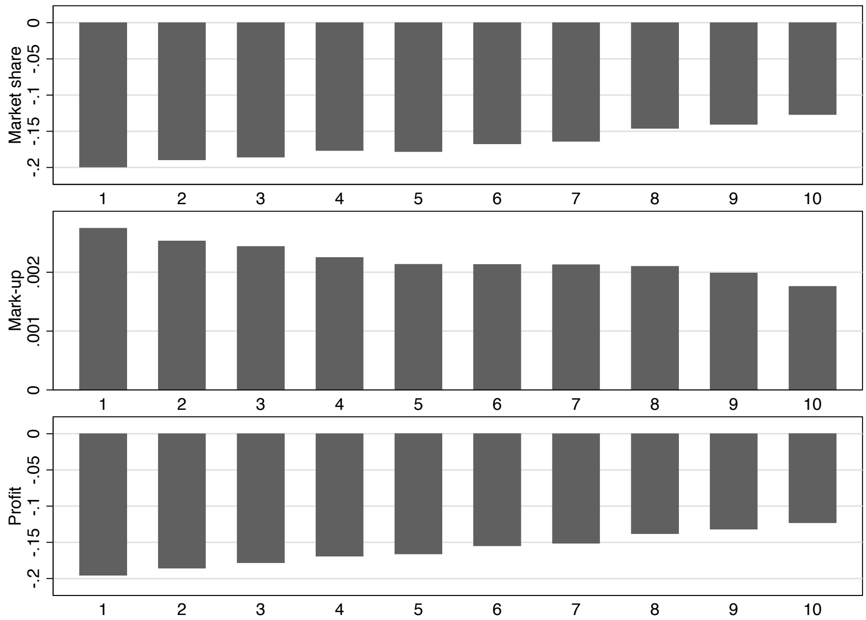

Figure 8: Effect of the China shock by price deciles (on French firms in 2010)

Notes: The figure reports the median log-change in market shares, mark-ups and profit for all French firms in 2010, separately for each price decile. The change is measured between the realized scenario and the counterfactual scenario in which China maintains its fundamentals from before 2001.

residual consumer of French products becomes less price-elastic. As a result, it is optimal for French firms to charge a higher mark-up for their product. Nevertheless, this effect is very limited, explaining the close relationship between market share loss and profit reduction.

Importantly, these effects are measured for firms that are present in our dataset in 2010. As such, these results do not take into account a potential extensive margin effect of the China shock: firms which lost the most from Chinese competition might have exited the industry and therefore not be in our dataset. Accounting for this extensive margin would probably amplify the dispersion in export performance across the price distribution, such that our results can be seen as a lower bound in terms of dispersion across firms.[32]

Given that low-quality firms are impacted more strongly by the China shock, quality upgrading is a natural remedy to mitigate this shock. We now turn to a scenario in which French firms are able to do so.

[32] Accounting for the entry and exit of firms would require to impose many additional assumptions regarding the fixed costs of exporting and the dynamic evolution of the fundamentals that drive the profit function of firms.

6.2 Accounting for quality adjustment

The demand system estimated in the previous sections provides a reason why firms would want to invest more in quality after a change in competition. In order to discipline and quantify the extent of this response, it is necessary to measure the cost of producing higher quality. As we emphasized in the description of the model, we assume that firms have idiosyncratic variations in the cost-elasticity of quality, but also that quality increase marginal costs through a quadratic relationship. Specifically, we have

$$\ln c_{jdt} = h_2 \lambda_{jdt}^2 + x_{jdt}\rho + \eta_{jdt}\lambda_{jdt} + \varphi_{jdt} \tag{15}$$

where parameter h_2 characterizes this quadratic form and η_{jdt} is the idiosyncratic cost-elasticity of quality. Under this specification, the first-order condition on quality in equation (10) implies the following quality chosen by the firm:

$$\lambda_{jdt}^* = \frac{1}{2h_2}\left(\frac{1}{\int \exp(\alpha(y,\nu))\,\omega_{jdt}^{(3)}(y,\nu)dy\,d\nu} - \eta_{jdt}\right) \tag{16}$$

Based on this first order condition, we can therefore implement the counterfactual experiment, taking into account the quality adjustment made by firm. First, we obtain estimates of quality $\hat{\lambda}_{fdt}$ and marginal cost $\hat{c}_{fdt}$ from the estimation. From the marginal cost equation (15), we can obtain measures of productivity $\hat{\varphi}_{jdt}$, and from the first order condition on quality, measures $\hat{\eta}_{jdt}$. Second, we implement our experiment by setting the prices and quality of Chinese producers to their pre-2001 levels. Third, we obtain the new prices, quality and marginal costs of all French firms under this new environment. In order to do so, we iterate over the first order conditions on quality and prices, and the definition of the marginal cost (15). We can then compare the market shares, profit and mark-ups between the two scenarios (fixed quality versus endogenous quality).

However, implementing this strategy requires the estimation of the marginal cost function and in particular the cost of quality through the parameter h_2.

Estimating the cost of quality Estimating the causal relationship 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.[33] As a consequence, even though the estimation delivers measures of marginal costs and quality, regressing marginal costs on these quality measures would likely underestimate the true cost of quality.

[33] See Kugler and Verhoogen (2012) for a model with complementarity between firms performance and quality choice, and empirical evidence of such a relationship.

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 its average residual consumer become less price sensitive, because 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 on quality as presented in equation (16). Because the position of the firm is endogenous, we compute the average price elasticity of each firm using weights from the first year the firm appears in the data. Specifically, our instrument is defined as

$$\begin{aligned} instr_{jdt} &= \frac{1}{\int \exp(\alpha(y,\nu))\tilde{\omega}_{jdt}(y,\nu)dyd\nu} \\ \text{with} \quad \tilde{\omega}_{jdt}(y,\nu) &= \frac{\tilde{\mathbb{P}}_{jdt}(y,\nu)(1-\tilde{\mathbb{P}}_{jdt}(y,\nu))e(y,\nu)F_{y,d}(y)F_{\nu}(\nu)}{\int \tilde{\mathbb{P}}_{jdt}(y,\nu)(1-\tilde{\mathbb{P}}_{jdt}(y,\nu))e(y,\nu)F_{y,d}(y)F_{\nu}(\nu)dyd\nu} \\ \tilde{\mathbb{P}}_{jdt} &= \frac{\exp(\delta_{jd0}+\mu_{jd0}(y,\nu))}{1+\exp(\delta_{jd0}+\mu_{jd0}(y,\nu))+\sum_{j'\neq j}\exp(\delta_{j'dt}+\mu_{j'dt}(y,\nu))} \end{aligned}$$

where date $t = 0$ is the first year at which firm f exports to destination d in the dataset. This instrument captures changes in the incentives of making quality from the change in the competitive environment. Firms differ in their initial weights, but the time variation of this instrument is only due to changes in the market shares of foreign countries that shift the average residual consumer faced by each French firm. Therefore, this instrument gives us exogenous variations in quality choices across time across firms, that allow us to identify the causal effect of quality on costs.

We present the results of this estimation in table 7. We regress the change in marginal costs on the change in quality to take advantage of the exogenous change from our instrument. Moreover, we add destination-year fixed effects to control for other aggregate factors that might explain changes in the competitive environment. Column 1 shows a positive correlation across French firms between the marginal cost of production and the quality of the product. However, the endogenous nature of product quality casts some doubts on the structural estimates identified from this correlation. To address this issue, column 2 reports the estimated cost elasticities from a 2SLS procedure using the first difference of our instrument in a first stage. As expected, we find a larger cost elasticity (0.24) using the instrumental procedure that identifies this parameter from exogenous changes in quality. Moreover, 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.

Table 7: Estimation results: marginal costs

	Dependent variable: $\Delta \log mc$				
	(1)	(2)	(3)	(4)	(5)
$\Delta\lambda$	0.15***	0.24***	0.30***	0.39***	0.34***
	(0.003)	(0.02)	(0.05)	(0.05)	(0.04)
$\Delta\lambda \times \lambda_{\bar{t}}$			0.0084		
			(0.006)		
$\Delta\lambda \times \lambda_{t_0}$				0.016***	
				(0.003)	
$\Delta\lambda \times \lambda_{t-1}$					0.013***
					(0.002)
R^2	0.37	0.24	0.32	0.31	0.33
FS F-stat		64.0	11.9	63.3	84.8

Notes: 59 822 observations. Firm-level clustered standard errors between parentheses. All specifications include destination-year fixed effects. Significance levels: * p<0.05, ** p<0.01, *** p<0.011.

The crucial parameter to quantify the quality response of French firms is the degree of convexity of the cost of quality. To estimate this parameter, we interact the change in quality with the average, initial and previous quality of the firm. In case of convexity, the larger the initial value of quality, the larger the cost of a quality increase. Our findings in columns (3)-(5) confirm this convexity. While the interaction using the average does not yield a significant coefficient, the interactions with the initial or previous quality returns a positive coefficient, that captures the convexity of the cost function. To summarize these values, we will use a value of 0.015 for the coefficient h_2 in our counterfactual experiment.[34]

Counterfactual results Having estimated the cost of quality, we are able to quantify the effect of the China shock on French exporters. In this scenario, we allow French firms to change the quality of their products, in order to adjust to the new competitive environment. In figure 9, we compare the log-change in market share, mark-up, profit and quality of French firms in different price deciles. Moreover, we show how endogenous quality affects these outcomes.

First of all, the bottom panel shows that all French firms upgrade their quality: as Chinese products gain market shares, consumers buying French products become richer

[34] To confirm that the relationship between marginal costs and quality is indeed quadratic, figure 14 in appendix B compares the fit of a quadratic and non-parametric regression between those two variables, and shows that the quadratic approximation performs well.

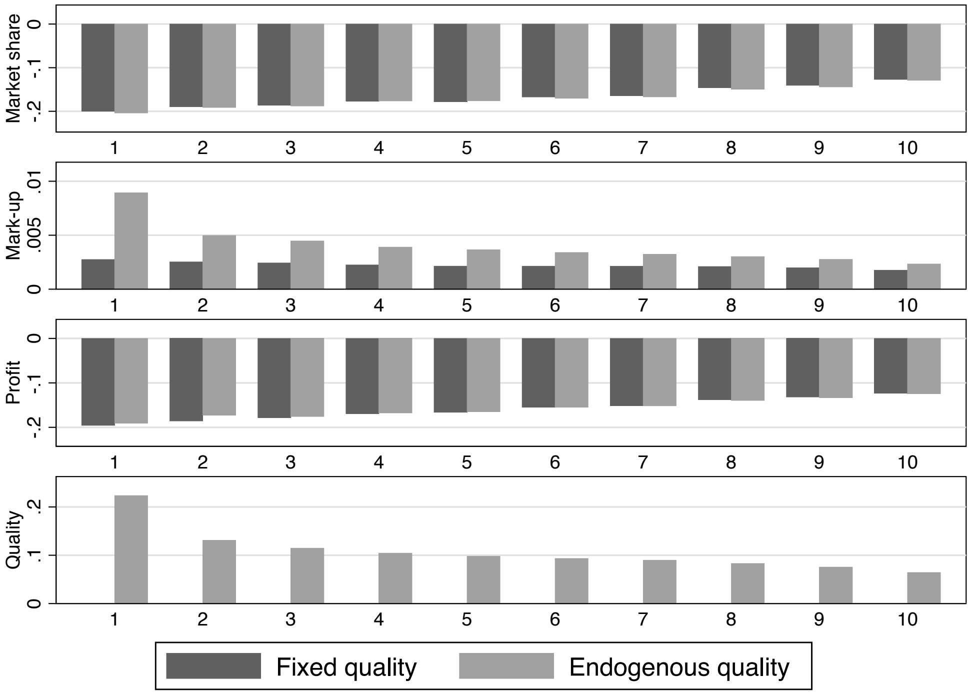

Figure 9: Effect of the China shock and the quality response

Notes: The figure reports the median log-change in market shares, mark-ups, profit and quality for all French firms in 2010, separately for each price decile. The change is measured between the realized scenario and the counterfactual scenario in which China maintains its fundamentals from before 2001.

and thus more willing to pay for quality. As a consequence, French firms upgrade the quality of their product, especially those with a low price initially. This quality increase is also reflected in mark-ups. We see that French firms tend to increase their mark-up as they increase their quality and face less price-elastic consumers.

However, the quality response of French firms appears to have a limited effect on profits. In fact, only firms at the bottom of the price distribution limit their losses by upgrading their quality, and 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 verify to which extent this increase in low-cost competition can replicate the unequal trend between low-price and high-prices shoe producers highlighted in figure 2. We run our model holding the characteristics of French exporters to their average pre-2001 levels. In other words, we quantify the evolution of French market shares that is only due to the change in the competitive environment. Figure 10 shows that most of the divergence in performance between high-price and low-price French firms is due to this change in competition rather than individual dynamics of French exporters.

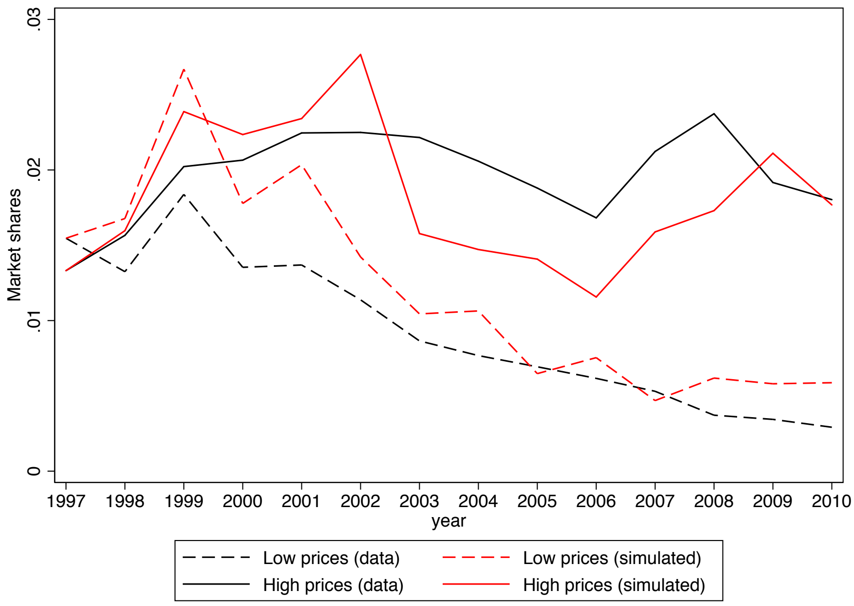

FIGURE 10: Role of the change in competition.

Notes: Simulated data points comes from running the model with the realized changes in foreign competition but holding individual characteristics of French exporters constant.

7 Conclusion

In this paper, we quantify the heterogeneous impact of foreign competition along the quality ladder. To achieve this, we estimate a demand system with heterogeneous consumer preferences. In particular, we allow price elasticity to vary across consumers, which generates stronger substitution patterns across firms with similar prices. On the supply side, firms can endogenously choose their product quality and we propose a strategy to estimate the cost of quality upgrading.

We estimate our model using export data from the footwear industry and find evidence of heterogeneity in consumers' preferences: rich consumers are less sensitive to prices and display higher preferences for French goods. As a way to understand how these patterns shape the impact of trade across firms, we implement counterfactual experiments on the "China shock". Over the period 2001-2010, We find that in terms of market shares, Chinese competition was twice more damaging to French firms at the bottom of the price distribution than at the top. Interestingly, the quality response of French firms did little to mitigate the impact of trade with China.

Overall, these results underline the importance of considering realistic substitution patterns to understand the impact of foreign competition on firm performance and decisions.

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Appendices

A Data Appendix

Our estimation mainly relies on two trade datasets: BACI and the French customs data. In both datasets, a unit of observation is a combination of a source, a destination country, a product category and a year. The main difference is that a source in BACI is an exporting country while a source in the French data is an exporting firm. In both datasets, we know for each observation the value of the shipment along with the physical quantity shipped.

This appendix describes the way we prepare the data for estimation.

Geographical Coverage We limit the set of source and destination countries to the 40 countries present in the WIOD database. For countries absent from WIOD, we are unable to implement the estimation as we cannot construct variables such as CIF prices or the market share of the outside good. Moreover, we also exclude France from the set of destination countries because we don't observe prices on the French market for French firms. Finally, because trade flows involving Luxembourg and Belgium are reported together in the raw trade data, we input all of Luxembourg trade to Belgium. All in all, our final dataset contains 38 destination countries (France and Luxembourg are excluded) and 39 origin countries (Luxembourg is excluded).

In the reduced form section of this paper, we study the impact of low versus high-cost competition on French firms. To classify these countries, we use the World Bank country classification from 2000. We consider as low-cost, any country that belongs to the low income or low-middle income categories from the World Bank classification. Table 8 summarizes the classification of countries as used in the paper.

Table 8: Country classification

Low cost	**Middle cost**	**High cost**		
Bulgaria	Brazil	Australia	Austria	Belgium
China	Czech Republic	Canada	Cyprus	Denmark
India	Estonia	Finland	Germany	Great-Britain
Indonesia	Hungary	Greece	Ireland	Italy
Latvia	Malta	Japan	Korea	Netherlands
Lithuania	Mexico	Portugal	Slovenia	Spain
Romania	Poland	Sweden	Taiwan	United States
Russia	Slovakia			
	Turkey			

Harmonization of product codes The product classification used by custom authorities is regularly updated to follow changes in product characteristics. We need to account for these changes to maintain a coherent set of product categories across time. To achieve this, we follow the procedure from Van Beveren et al. (2012) who apply the methodology from Pierce and Schott (2012) to European statistics. This allows us to obtain consistent product categories from 1997 to 2010.

Product information in BACI is at the 6-digit level of the HS classification. We label "HS6+" the time-invariant classification obtained from applying Pierce and Schott (2012)'s algorithm at the HS6 level.

Product information in the raw French customs data is reported at the 8-digit categories of the combined nomenclature. This classification is nested into the HS6. We aggregate customs data at the HS6 level and then convert it to HS6+ to make it consistent with BACI.

Choice of units for quantity information The customs statistics from France allows exporters to declare shipped quantities in two different units: one unit is the weight, the other one is a supplementary unit that is product specific and often more relevant to describe the quantities of certain types of goods (e.g. the number of bottles for wine or the number of pairs for shoes). By contrast, quantities in BACI are only reported in weights.

In order to both datasets homogeneous, we use observations in French customs data for which both measures of quantities are declared and compute a product-specific conversion rate from supplementary units to weight. We first proceed by applying Pierce and Schott (2012) algorithm to convert the raw customs data from the 8-digit level of the combined product nomenclature to a time-invariant product classification that we label "CN8+". Then, we compute the average log-difference between both quantities by CN8+ category.

For any CN8+ product where the conversion rate is computed with enough precision,[35] we replace missing weights by applying the conversion rate to supplementary units. It is only after this operation is completed that we aggregate the French customs data first from CN8 to HS6 and then to HS6+, as described in previous paragraph "Harmonization of product codes".

Constructing Prices We use unit values - the ratio between the value and the weight of a trade flow - as a proxy for prices. Since we want to use our trade data to estimate a demand system, we need to construct prices which are as close as possible to those

[35]In COMTRADE, the database used to construct BACI, quantities are also reported in two units. We follow the procedure used to convert quantities to weight in BACI. Namely, we only compute a conversion rate for product with at least 10 trade flows with quantities reported in both units and with a standard deviation of the log-difference smaller than 2.5. See Gaulier and Zignago (2010) for further details on the construction of BACI database.

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 WIOD. These data contain bilateral free-on-board (FOB) value and transportation costs at the 2-digit level of the Statistical classification of products by activity (CPA) from 1995 to 2011. 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.

Data Cleaning Information on prices in trade data is known to be noisy. In order to mitigate this issue, we drop prices with extreme values. In order to detect extreme prices at the country-level, we estimate the following regression:

$$\ln p_{sdpt} = FE_{sd} + FE_t + FE_p + e_{sdpt}$$

with $\ln p_{sdpt}$ the log export price of a country s exporting HS6+ product p to destination country d. For observations such that the error term $\hat{e}_{sdpt}$ is larger than 2 in absolute value, we substitute the actual price $\ln p_{sdpt}$ with predicted price $\ln \hat{p}_{sdpt} = FE_{sd} + FE_t + FE_p$.

In order to detect extreme prices at the firm-level we run the following regressions:

$$\begin{aligned} \ln p_{fdpt} &= FE_{dpt} + u_{fdpt} \\ \ln p_{fdpt} &= FE_{fp} + FE_t + v_{fdpt} \end{aligned}$$

where f identifies a French exporting firm. We drop observations such that $\hat{u}_{fdpt}$ is larger than 3 in absolute value or $\hat{v}_{fdpt}$ is larger than 2 in absolute value.

Finally, we drop destination-HS6+-year markets served by less than 5 firms. The focus of our paper is on distributional effects across French firms within market. Therefore, it makes little sense to keep these markets where distributional effects are mechanically constrained by the small number of firms, and markets shares are likely to be very volatile.

Market Share and Price of the Outside Good In order to implement the estimation, we need information regarding the outside good in each market (the domestic variety in our context). At the two-digits level of the CPA classification, we construct the market share of the outside good by computing the share of domestic consumption in total consumption from the WIOD database. We then convert these domestic shares to HS6 and HS6+ using a correspondence table available on RAMON Eurostat's Metadata Server.

The estimation also requires to know the price of the outside good. However, the price of the domestic variety is not available in our international trade data since goods don't cross a border. In order to proxy the price of the domestic good in a given country and year, we use the price of its exports as measured in the BACI dataset. However, since we observe this price for many destinations, we infer the domestic unit values by regressing the logarithm of the FOB unit value on a set of fixed effects:

$$\ln p_{sdpt}^{fob} = FE_{sp}^{(1)} + FE_{st}^{(2)} + FE_{pt}^{(3)} + FE_{dt}^{(4)} + \varepsilon_{sdpt}$$

such that we can separate variations in prices across origin, product, destination and time. From this specification, we construct the domestic price $\ln \hat{p}_{sdpt}^{fob}$ as

$$\ln \hat{p}_{sdpt}^{fob} = \hat{FE}_{sp}^{(1)} + \hat{FE}_{st}^{(2)} + \hat{FE}_{pt}^{(3)}.$$

Product Characteristics Although we construct the data including all sectors, we only estimate our model on eight hs6 positions within the hs2 position number 64: 'Footwear; Gaiters and the like; parts of such articles'. Table 9 reports the list of 6-digit categories in the hs2 number 64, indicating for each product if they are included in the estimation. Using the literal description of each product, we manually code four product characteristics: 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*). Table 9 also reports the value of these dummies for each product.

Income Distribution Our estimation requires information on income distribution. We obtain information on income per capita and the Gini index by destination country from the World Bank. In order to feed this information into the estimation, we assume that income distribution is log-normal. This distribution is convenient because it makes it possible to recover the mean μ_{y_d} and standard deviation σ_{y_d} parameters from the average income per capita m_{y_d} and Gini Index Λ_{y_d}, through following formula

$$\begin{aligned} \sigma_{y_d} &= \sqrt{2}\Phi^{-1}\left(\tfrac{1+\Lambda_{y_d}}{2}\right) \\ \mu_{y_d} &= \ln m_{y_d} - \tfrac{1}{2}\sigma_{y_d} \end{aligned}$$

Table 9: 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				

B Additional results

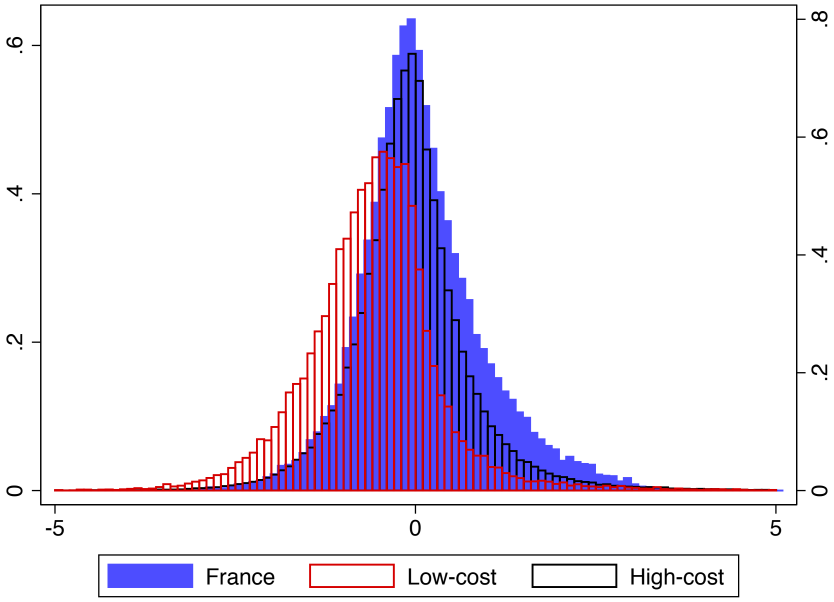

Figure 11: Distribution of Export prices

Notes: This figure shows the distribution of export prices, expressed in log-difference to the mean price in the destination-HS6-year market. Each observation is weighted by its market share in the destination-HS6-year market.

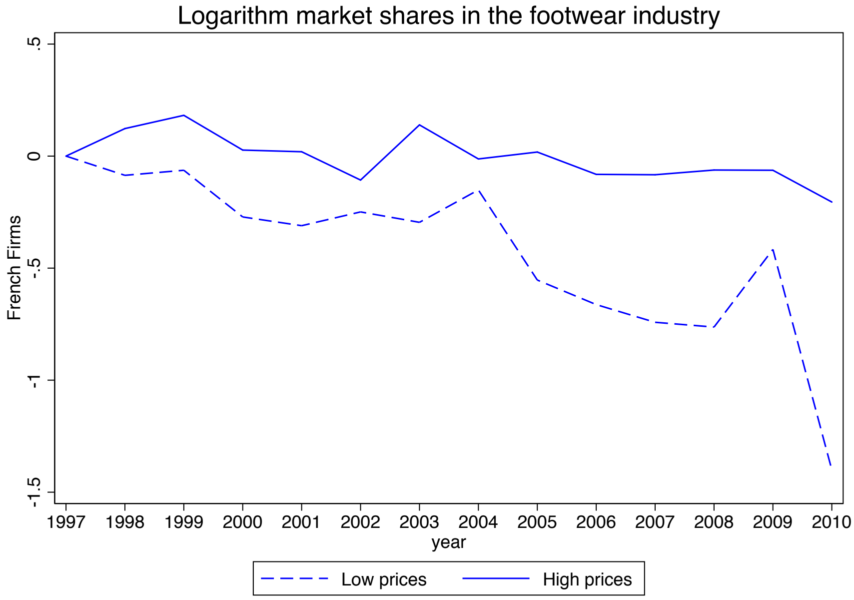

FIGURE 12: low-cost French shoe producers have suffered more than expensive shoe producers.

Notes: This figure shows the change in the log market share since 1997, $\ln s_{fdpt} - \ln s_{fdp97}$ *for high-price and low-price shoe manufacturer. High-price and low-price observations respectively belong to the fourth and first quartiles of the distribution of average prices before 2001.*

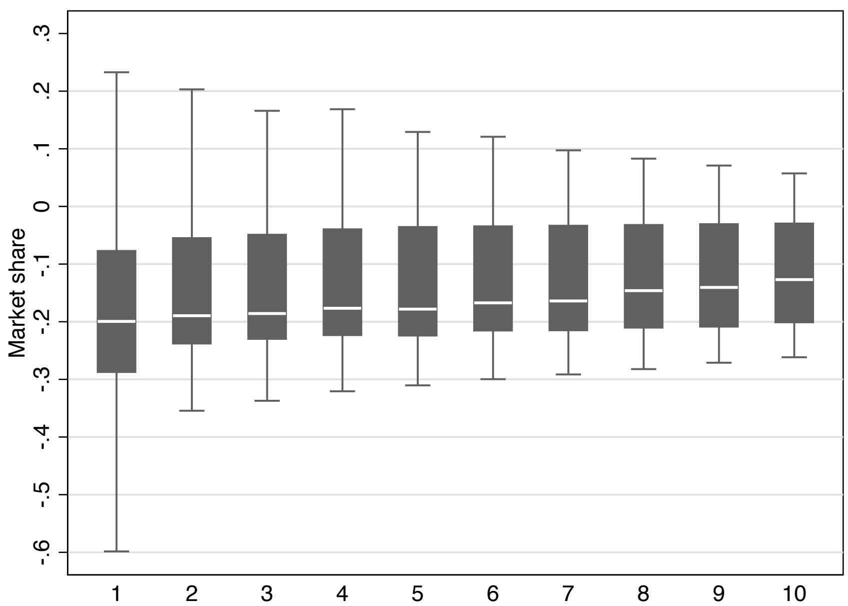

FIGURE 13: Effect of the China shock on market shares by price deciles (on French firms in 2010)

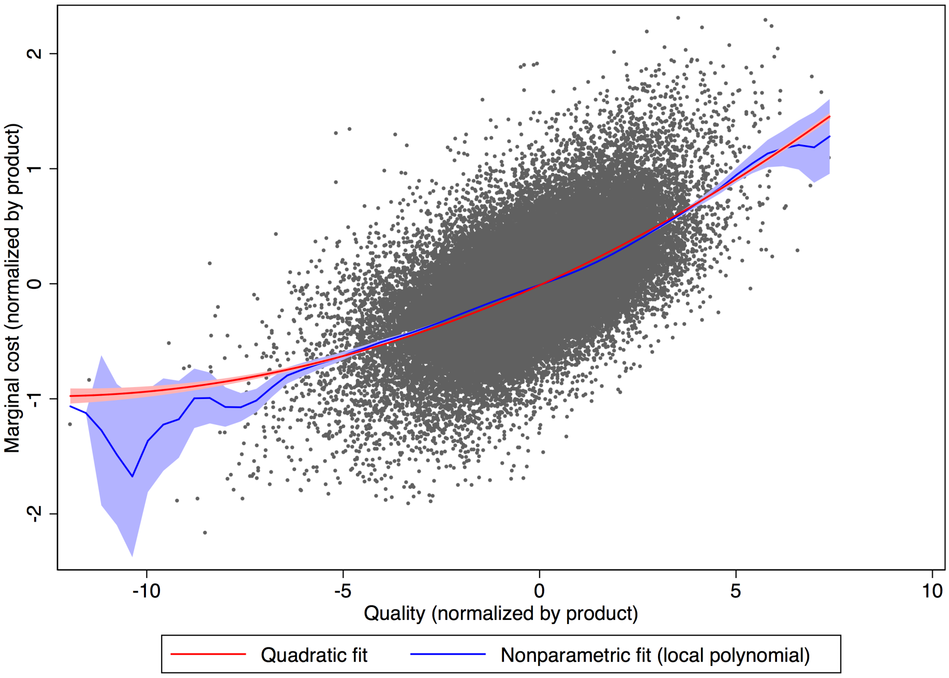

FIGURE 14: Relationship between marginal cost and product quality