Foreign Competition along the Quality Ladder*

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November 2018

Abstract

We document that French firms with low prices are more affected by low-cost competition than high-price firms. We rationalize this finding through a random-coefficients demand model with heterogeneous consumers. This heterogeneity generates rich substitution patterns across producers and leads to quality upgrading 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 50 percent more damaging to French firms at the bottom of the price distribution, and show that quality upgrading did little to mitigate that impact.

*We are grateful to Amit Khandelwal, Thierry Mayer, John Morrow, Eric Verhoogen, David Weinstein and seminar and conference audiences at Johns Hopkins, Columbia, Carlos 3, Kent, Birkbeck universities, ETSG 2017, EIIT 2017, SED 2018 and the Midwest International Trade Conference 2018 for numerous comments and discussions. This paper was previously circulated under the title "The Impact of Chinese Competition along the Quality Ladder". We thank CNIS and French customs for confidential data access.

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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.

[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 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 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 and serving an appealing product. The optimal quality chosen by a firm depends on its idiosyncratic cost of producing quality and the inverse of its weighted average demand elasticity: firms facing price-inelastic consumers will optimally choose to produce higher quality goods. As a consequence, any change in the competitive environment that modifies a firm's average price elasticity will induce a change in the optimal product quality of that firm. For instance, an increase in low-cost competition that appeals to elastic consumers will imply a reallocation of French market shares toward inelastic consumers, encouraging French firms to produce higher quality product.

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 import tariffs and exchange rates to instrument country-level prices and average

[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.

exchange rates on firms' imports to instrument firm-level prices. 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 than existing papers estimating demand in international trade, we can capture 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 competition. However, estimating the quality response of firms from changes in their average price-elasticity presents identification challenges: any endogenous change in product quality will induce a movement along the quality ladder and a change in the set of consumers served by the firm. Therefore, a naive regression of quality on this average price-elasticity will overestimate the impact of competition on quality. Fortunately, our model delivers exogenous variation in the price-elasticity faced by French firms: because the effects of competition are heterogeneous along the quality ladder, we can isolate changes in this price-elasticity that is only due to changes in the competitive environment. Therefore, we can consistently estimate the quality response of French firms from these exogenous changes in their set of consumers.

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 30 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. Finally, we find that consumers display idiosyncratic preferences for other characteristics as well as their preferences for French goods. This result implies stronger substitution patterns between French firms and varieties that share the same characteristics.

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 prices 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 quality response from 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. We show that both measures respond to exogenous change in the average price elasticity: as competition reallocates consumers between varieties, firms loosing price-elastic consumers for inelastic consumers tend to optimally increase their quality and their marginal cost.

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 more than 50 percent larger at the bottom of the price distribution relative to the top: increase in Chinese competition generates a median 16 percent loss in market shares for the first decile in the price distribution. Meanwhile, firms in the highest price decile records a median 9 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 insignificant amount across price deciles, due to the large costs associated with quality upgrading.

Our work relates to the literature estimating firm's product quality using trade data. Roberts, Xu, Fan, and Zhang (2017) and Hottman, Redding, and Weinstein (2016) estimate demand functions at the microeconomic level in order to disentangle price-competitiveness from non-price competitiveness in the dispersion of export performance.[3] 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,

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

e.g. better access to high quality inputs (Fieler, Eslava, and Xu, 2018; Bas and Strauss-Kahn, 2015); 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 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 heterogeneous impacts across consumers of changes in product prices. Closer to our paper, Adao, Costinot, and Donaldson (2017) and Heins (2016) introduce mixed preferences to generate heterogeneous patterns of substitution at the aggregate level. In contrast to these papers, we use micro data to estimate realistic substitution patterns across firms, which allows us to quantify the heterogeneous effects of low-cost competition across French firms, and measure their quality response.

Finally, our 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 between standardized and specialized goods. Our paper differs in that we rely on a structural approach that allows us flexibly estimate these substitution patterns from the data.

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 independence of irrelevant alternatives (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.[4] The information is disaggregated at the firm, year, destination or origin country and eight-digit product category of the combined nomenclature (CN8).[5] The second source of trade data is BACI database, developed by 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 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

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

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

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 strategy similar to the one 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) values 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.[6] 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 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.[7]

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.

[6] 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.

[7] Precisely, we run regressions of log prices on destination fixed effects or firm-product-year fixed effects and eliminate observations whose 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 with different positions in the price distribution are differently affected by foreign competition.

In order to highlight these heterogeneous effects, 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:[8]

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

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 over the period. To do so we compute, for each six-digit product category, the change in the global market share of low-cost countries between before 2001 and after 2006.[9] 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

[8]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.

[9]We classify as "low-cost" countries that belong to the low or middle-low income grouping from the World Bank. See table 6 in appendix A for details.

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 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.

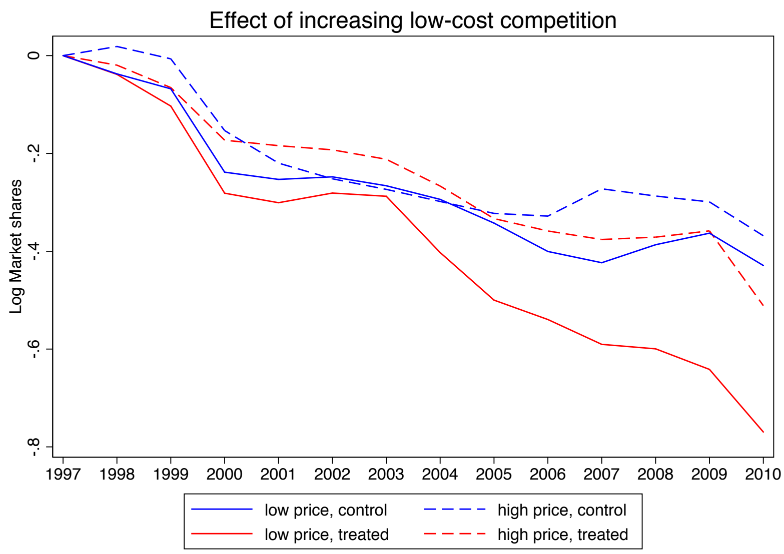

FIGURE 1: Low-cost competition impacts low-price varieties more.

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.[10] In column (1), we

[10] 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.

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 markets 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 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.[11] 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

[11] Once again, we rely on the classification from the World Bank to categorize a country as high-cost. See table 6 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.

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 than high-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.

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 closer substitutes. This property arises from the presence of heterogeneous consumers which differ in their preferences over product characteristics. In addition to capturing complex substitution patterns, the presence of heterogeneous consumers generates further 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.[12] 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 distribution, the probability that consumer i in destination d buys variety j is

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

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 $(K+1)\times(K+1)$ diagonal matrix of parameters and ν_i is a $K+1$ column-vector of random variables. Equa-

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

tion (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 follow a normal distribution based on the income distribution in each destination market d.[13] Moreover, we assume that each ν_i follow a standard normal distribution. Therefore, we allow consumers' preferences for prices and other characteristics to vary according to their income and other unobserved source of variations.

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 pick 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

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

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 Firm's Problem

Having described demand fundamentals, we can now turn to the supply side and present the problem of the firm. Importantly, we do not need to specify this supply side to estimate the demand system. The specification and assumptions made in this section are only necessary to perform the counterfactuals implemented in the last section of the paper: since these counterfactual experiments quantify the endogenous quality response of firms to a change in competition, they require to measure the cost of producing higher quality products.

In each destination, a firm sets price and product quality to maximize its

[13] For each country, we translate information on the GDP per capita and Gini indices to first and second moments of a log-normal distribution. See appendix A for details.

profit function. We start by defining the cost and profit functions of the firm, before deriving the optimal choices of price and quality.

Cost and profit functions 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

$$\ln c_{jdt}(\lambda) = x_{jt}\rho + \eta_{jdt}\lambda + h\lambda^2 + \varphi_{jdt}. \tag{6}$$

Product characteristics affect production costs through the vector of parameters ρ. Moreover, we assume that quality enters the marginal cost function through an idiosyncratic quality-elasticity of costs η_{jdt} and a quadratic term $h\lambda^2$. This convexity in the cost of quality is necessary to generate a finite quality choice by firms, and will be verified empirically.[14] 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.

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 solving their respective first order conditions on profit.[15]

Optimal pricing Firm optimal pricing rule is

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

[14] 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.

[15] 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.

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 are 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, higher quality raises 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.

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

Given the marginal cost function, this first order condition leads to the following optimal quality in each destination:

$$\lambda^*_{jdt} = \frac{1}{2h}\left(\frac{1}{\int \exp(\alpha(y,\nu))\,\omega^{(3)}_{jdt}(y,\nu)dy\,d\nu} - \eta_{jdt}\right) \tag{10}$$

with $\omega_{jdt}^{(3)}(y,\nu) \equiv \frac{e(y)(1-\mathbb{P}_{jdt}(y,\nu))\mathbb{P}_{jdt}(y,\nu)F_{y,d}(y)F_{\nu}(\nu)dyd\nu}{\int e(y)(1-\mathbb{P}_{jdt}(y,\nu))\mathbb{P}_{jdt}(y,\nu)F_{y,d}(y)F_{\nu}(\nu)dyd\nu}$. This expression summarizes the determinants of firm product quality. First, the optimal quality set by a firm depends on its cost-elasticity: firms with a small η_{jdt} are able to produce quality products at a relatively low cost and therefore choose a higher level of quality. Second, the quality decision depends on the type of consumers the firm faces. Specifically, the lower the price-elasticity of their consumer, the more firms are willing to increase their cost through quality upgrading. 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 residual consumers. As such, foreign competition can trigger quality adjustments by firms. It is important to note that this mechanism would not be at play in the absence of heterogeneity across consumers. Without heterogeneity, low-cost competition does not change the composition of firm sales across consumer and leaves untouched firms' optimal quality.

Finally, equation (10) highlights the importance of the parameter h that characterizes the convexity of the cost function. The value of this parameter disciplines the quality response of firms to a change in competition. Therefore, it will play a key role in shaping the results of the counterfactual experiments. In next section, we present our strategy to estimate the model, and in particular the distribution of price elasticity across consumers and the degree of convexity of quality in the marginal cost function.

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 estimation of the demand side and finally we describe our strategy to estimate the supply side, and in particular the cost of quality upgrading.

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.[16]

We pick the footwear industry mainly for two reasons. First, shoes are a well-defined consumer good. This allows us to obtain prices that are consistent across varieties, and product characteristics that can be inferred from the data. In particular, we create four product characteristics for the estimation from the product codes descriptions: 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 the coding of product characteristics.

The second reason for the relevance of the footwear industry is that it mimics the recent trend 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.[17]

To portray a more comprehensive picture of the global changes at play in the footwear industry, we look at the change 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 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 within-firm increases of the price charged by French shoes. Both of these mechanisms suggest heterogeneous impacts of low-cost competition along the price dimension.

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 section 2, 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,

[16] The list of the included and excluded product codes is reported in table 7 in appendix A.

[17] 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.

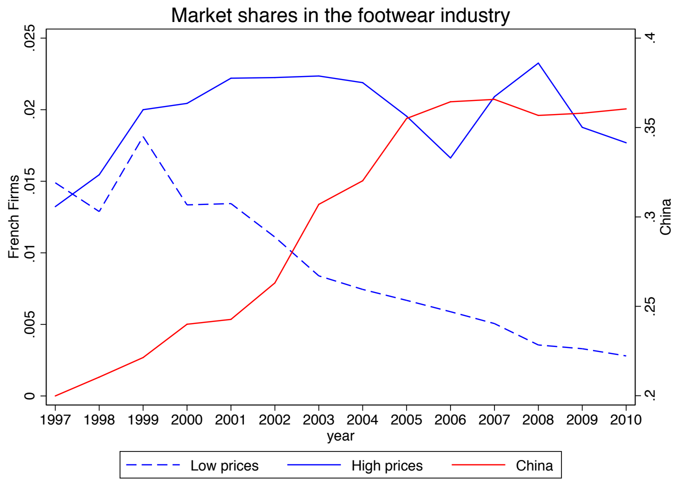

FIGURE 2: Chinese competition Hits Cheap Shoes Harder

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.

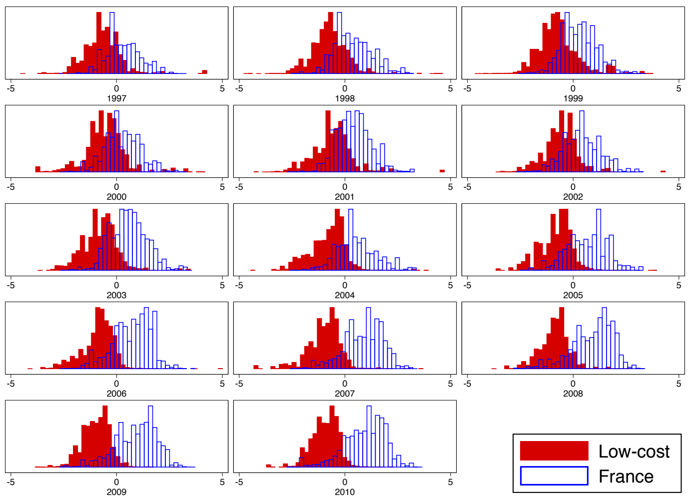

FIGURE 3: The price of French shoes diverge from low-cost competition

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.

and correct extreme prices from other countries' exports.[18] This cleaning procedure leaves us with 192 548 observations during the sample period, out of which 102 250 are French. In table 3, we report summary statistics for the 2 388 French

[18]These different steps are described in A.

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%.

TABLE 3: Summary statistics for French firms

	Mean	*p5*	*p25*	*p50*	*p75*	*p95*
By firm:						
# observations	42.8	2	3	10	33	180
# destinations	5.9	1	2	3	7	20
# products	2.7	1	1	2	4	7
Price	76.7	8.9	21.1	40.4	83.7	267.5
Market share (%)	0.005	$2.6e^{-6}$	0.00004	.0003	.002	.02

Notes: FOB Prices per kilogram in Euros. Sample of 2388 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.[19] 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:

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

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.

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

4.2 Demand Side Estimation

We start by presenting the instruments used to account for price endogeneity. Then, we move to the description of the algorithm to compute the estimator.

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.

The use of international trade data provides a good set of instruments through the existence of exchange rates and import tariffs between countries. Exchange rates and tariffs directly affect the final price charged by a firm in foreign markets. Moreover, since exchange rates fluctuate following macroeconomic conditions, and tariffs vary for institutional reasons, they are unlikely to be correlated with demand shocks or quality decisions made by individual shoe producers. Therefore, these variables are valid instrument to identify the price elasticities in our demand system.[20] Specifically, we use exchange rates data from the IMF and tariffs data from the Market Access Map (MAcMap) dataset that provides bilateral measures of applied tariff duties.[21]

However, the use of exchange rates and tariffs as instruments is not sufficient to estimate the model. Since we have 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 instrument for

[20] See Khandelwal (2010) or Hallak and Schott (2011) for a similar use of exchange rates, and Fontagné et al. (2018) using tariffs.

[21] Appendix A provides details on the dataset.

French firms.[22] 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 capture the prevalence of imports flows in the total costs of the firm. Therefore, we obtain four instruments that exploit movements in exchange rates as exogenous shifters in the production costs of firms. These movements generate prices adjustments while being plausibly orthogonal to demand shocks or endogenous quality decisions made by firms. As such, they are ideal instrumental variables to identify price elasticities of demand.

Demand estimation algorithm In this paragraph we describe the estimation of parameter $\theta \equiv \{\alpha, \Pi, \Sigma\}$ which governs the distribution of random coefficients, as described in equation (2). Parameters are 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

$$E\left[z_l \, \varepsilon(\theta_0)\right] = 0, \qquad \text{for} \quad l = 1, .., L \tag{11}$$

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.

[22] See Piveteau and Smagghue (2018) for further discussion on these instruments.

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 vector of predicted market shares $s(\delta, x, \ln p; \theta)$ equals the vector of 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

$$\delta^{(h+1)} = \delta^{(h)} + \log S - \log s(\delta^{(h)}, x, \ln p; \theta). \tag{12}$$

We iterate until the minimum of the vector of squared difference between $\delta^{(h+1)}$ and $\delta^{(h)}$ is less than 10^{-12}.[23] Moreover, we use 500 draws from 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 on the non-linear parameters θ. We then regress $\delta(S, x, \ln p; \theta)$ on product characteristics x and firm dummies γ, to estimate the remaining parameter β that appear in the utility function. Finally, we obtain the structural errors of the model from

$$\hat{\xi} = \delta(S, x, \ln p; \theta) - \hat{\beta}x - \hat{\gamma} \tag{13}$$

to 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 linear instrumental variables regression, hence reducing the dimensionality of the search algorithm.[24]

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 $\xi(\theta)$. Formally, we have

$$\hat{\theta} = \text{argmin}_{\theta} \quad \xi(\theta)' Z \Phi Z' \xi(\theta) \tag{14}$$

where Φ is a weighting matrix. Practically, we obtain our GMM estimates in two steps and construct standard errors that are clustered at the producer level.

[23]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.

[24]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.

First, we use $\Phi = (Z'Z)^{-1}$ to obtain a first estimate $\tilde{\theta}$. From this estimate, we construct the optimal weighting matrix $\Phi = \tilde{\Lambda}^{-1}$ where $\tilde{\Lambda}$ accounts for the panel structure of the data. Specifically, we have

$$\tilde{\Lambda} = \sum_{c=1}^{C} u_c' u_c \quad \text{and} \quad u_c = \sum_{i \in c} \xi_i(\tilde{\theta}) Z_i$$

where C is the total number of producers (firm or country) and i denotes an observation. We then minimize our objective function using this new weighting matrix and obtain standard errors for our estimator using the GMM standard errors from Newey and McFadden (1994). Specifically, the estimated variance of our estimator is

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

where Φ is the optimal weighting matrix estimated in the first stage, G is the gradient of the objective function and $\hat{\Lambda}$ is the estimator of the covariance matrix of the vector of moments defined above, using our new GMM estimates $\hat{\theta}$. Clustering these standard errors is crucial to account for the so-called Moulton problem that may arise in our context: since our instruments only vary at the producer level, it is necessary to account for this sampling structure in the error of our estimates.

Having estimated the parameters of the model, we can extract several objects of interest. First, we obtain a measure of quality $\lambda_{jdt} \equiv \hat{\xi}_{jdt} + \hat{\gamma}_f$ for each variety j in destination d. Second, we can derive the optimal mark-up charged by a firm in a destination market. This object, entirely based on the demand system as shown in equation (8), allows us to recover the marginal costs of production: since prices are observed in the data, constant marginal costs can be obtained by deducting the estimated mark-ups from the observed prices. Therefore, it is important to note that the supply-side of the model is not used to estimate the demand system. Instead, we first recover marginal costs from the demand estimation, and then estimate the marginal costs parameters. We now describe this estimation of the supply side.

4.3 Supply Side Estimation

The estimated demand system 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. Specifically, the first order condition on quality highlights the importance of the convexity in the cost function, through the parameter h, in shaping this response.

Fortunately, the model provides guidance on how to estimate this parameter. From the first-order condition on quality, we have

$$\lambda^*_{jdt} = \frac{1}{2h}\left(\tilde{\alpha}^{-1} - \eta_{jdt}\right) \quad \text{with} \quad \tilde{\alpha}^{-1} \equiv \frac{1}{\int \exp(\alpha(y,\nu))\,\omega^{(3)}_{jdt}(y,\nu)dy\,d\nu}$$

such that the parameter h can be estimated from the regression of the quality measure λ on the weighted inverse of the elasticity of demand $\tilde{\alpha}^{-1}$. Alternatively, combining the marginal cost function and the first order condition on quality leads to the following formulation of the marginal costs:

$$\ln c_{jdt} = x_{jt}\rho + \frac{1}{4h}\left(\tilde{\alpha}^{-1}\right)^2 - \frac{1}{4h}\eta^2_{jdt} + \varphi_{jdt}.$$

Therefore, the model provides two relationships between objects that can be recovered from the estimated demand system: the quality measure, the inverse average elasticity of demand, and the marginal cost.

However, the correlations between these objects certainly does not consistently identify h because of simultaneity issues: changes in the inverse of the average price-elasticity $\tilde{\alpha}^{-1}$ can be due to changes in competition but also to changes in quality itself. In particular, a reduction in the cost of producing quality η_{jdt} would make a firm move up the quality ladder and reduce its average price elasticity. To circumvent this endogeneity issue, we design an instrument for $\tilde{\alpha}^{-1}$ that captures changes in the average price elasticity due to changes in competition. As such, this instrument is orthogonal to changes in quality or cost that are based on variations in η_{jdt} or φ_{jdt}, the residuals of the regressions. Specifically, we construct an inverse weighted price elasticity for a variety that only varies due to changes in characteristics of its competitors:

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

where $\delta_{jd\cdot}$ denotes either the average or initial δ of producer j in destination d. This instrument captures changes in the incentives of making quality from the change in the competitive environment. Firms differ in their average or initial characteristics, but the time variation of this instrument is only due to changes in the characteristics of competitors , $\sum_{j' \neq j} \exp(\delta_{j'dt} + \mu_{j'dt}(y, \nu))$, that shift the average residual consumer faced by each French firm. Therefore, this instrument gives us exogenous variations in the average price elasticity, that triggers quality responses and marginal cost responses.

We use this instrument to consistently estimate the relationship between quality and average price elasticity, and between marginal cost and the square of the average price elasticity. We obtain two estimates of h from these regressions that will guide us in the parametrization of our counterfactual experiment.

5 Demand Estimation Results

In this section, we first describe the results of the demand estimation. We then discuss several outcomes of the model to showcase how the demand system realistically captures heterogeneity across firms. Finally, we present estimates of the cost of producing quality, which will allow us to discipline the counterfactual experiment performed in the next section.

5.1 Demand Estimation Results

Table 4 describe the estimation results from several demand specifications. In columns (1) and (2), we first report results from a logit demand system: we regress the normalized logarithm of the market share $\log s_{fdpt} - \log s_{0pdt}$ on product characteristics, log of price and an interaction between the log of the price and the average log income in the destination. Moreover, we include firm-specific dummies, such that the average valuation of French products cannot be identified. While the OLS regression in column (1) displays unrealistic positive price elasticity estimates, column (2) validates our instrumental variables strategy. First, the first stage F statistics shows that our set of instruments is strongly enough correlated with prices. Second, we obtain realistic price elasticities, equal to -2.89 on average and positively correlated with the average log income of the consumer in the foreign destination.[25]

We now turn to the specifications with random coefficients. Specification (3) introduces random coefficients on the price elasticity and the preference for French goods. Following equation (2), coefficients in column Π indicate the effect of the log income on the parameter, while coefficients in column Σ capture the role of unobserved heterogeneity generated by shocks from a standard normal

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

Table 4: Estimation results

	OLS (1)	2SLS (2)	Random coefficients (3) Mean	(3) Π	(3) Σ	(4) Mean	(4) Π	(4) Σ
log price	0.20***	−1.89***						
	(0.057)	(0.24)						
log price × inc_d	0.41***	0.74***						
	(0.054)	(0.22)						
α			1.15***	−0.44***	−0.17	0.67***	−0.28***	−0.31**
			(0.11)	(0.089)	(0.25)	(0.12)	(0.098)	(0.15)
French			.	−0.37*	3.94***	.	−0.39**	2.28***
				(0.21)	(0.37)		(0.17)	(0.30)
Leather sole	−1.05***	−1.13***	−1.23***	.	.	−9.61***	0.50**	6.95***
	(0.11)	(0.14)	(0.12)			(1.53)	(0.23)	(0.96)
Leather top	1.17***	0.97***	0.90***	.	.	0.89***	0.49***	0.53
	(0.11)	(0.12)	(0.11)			(0.098)	(0.16)	(0.59)
Fabric top	−0.048	−0.023	−0.028	.	.	−0.29	0.51***	-0.18
	(0.079)	(0.098)	(0.096)			(0.29)	(0.13)	(1.43)
Boot	−0.58***	−0.58***	−0.54***	.	.	−0.59***	0.038	-0.35
	(0.060)	(0.064)	(0.062)			(0.083)	(0.067)	(0.43)
R^2	0.55							
First stage F-stat		34.2						

Notes: Number of observations: 192 548. Standard errors between parentheses clustered at the producer level. All specifications include producer (firm or country) fixed effects. Instruments include the exchange rates and import tariffs 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.

distribution.[26] In addition to heterogeneity in price-elasticity and preferences for French goods, specification (4) includes random-coefficients on product characteristics that can vary with income (through parameters Π) and unobserved shocks (with parameters Σ). Specifications (3) and (4) also include firm-specific dummies, which explains that the mean valuation of French products is not identified.

Both specifications emphasize the importance of allowing for heterogeneity in preferences. First of all, the average price elasticity, $-\exp(\alpha)$, is comprised between -2 and -3, which is consistent with the 2SLS specification. Moreover, we can see in both specifications that richer consumers are significantly less price-elastic (coefficient Π_α) and tend to have a lower preference for French goods (coefficient Π_{French}). While we did not have prior regarding the effect of income on the taste for French goods, it is certainly reassuring that richer consumers display lower price-elasticity of demand. Similarly, specification (4) shows that income also plays a role in shaping preferences for product characteristics: we

[26] We draw different random shocks for each variables such that each parameter Σ is identified from different consumer-specific shocks.

find that richer consumers value disproportionally more soles and tops made of leather and shoe tops made of fabric.

Table 4 also documents the dispersion in preferences driven by other types of heterogeneity. First, specifications (3) and (4) shows that some consumers have specific preference for French goods and for sole made in leather. The existence of positive coefficients for the parameters Σ associated with these characteristics, implies stronger substitution patterns for varieties sharing those characteristics. Therefore, French varieties display stronger substitution between them than with foreign varieties. Moreover, we do find in specification (4) that consumers have different price-elasticity driven by factors that are different than their income. This heterogeneity will further generate patterns of substitution between varieties that are increasing with their proximity in the price space.

Having documented these results, we further describe the implications of these heterogeneous preferences by describing several outcomes of the model. For the rest of paper, we use specification (4) that includes random coefficients on all characteristics.

5.2 Demand 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.

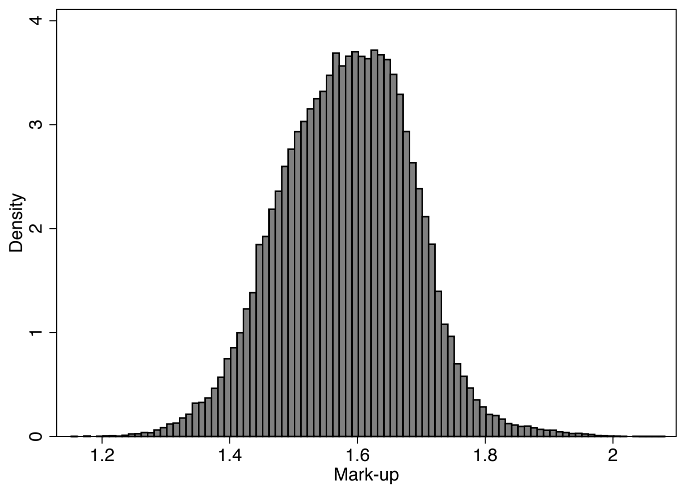

FIGURE 4: Distribution of mark-ups of French firms

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 at a given time. These mark-ups are directly computed from equation (8) using the parameter estimates and the distribution of consumer characteristics. The average mark-up is around 60% which is at the higher end of estimates found in the literature, which 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%.

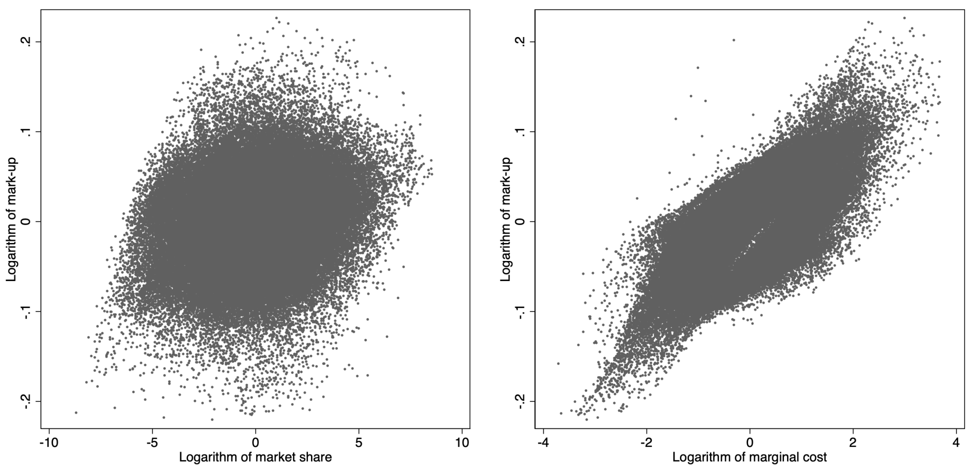

FIGURE 5: Correlation of mark-up with market share and marginal cost

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 mark-up 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.

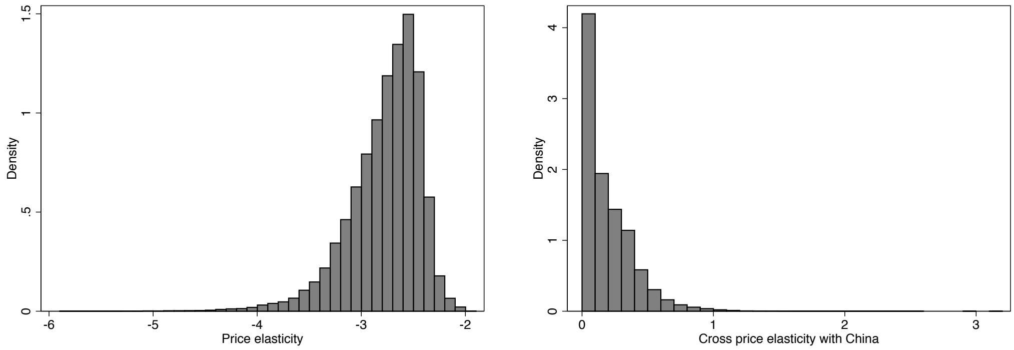

FIGURE 6: Distribution of own and cross-price elasticities (French firms).

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. From the figure, we can see a large dispersion in price-elasticity, ranging from 2 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 positive cost 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.[27] 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.[28]

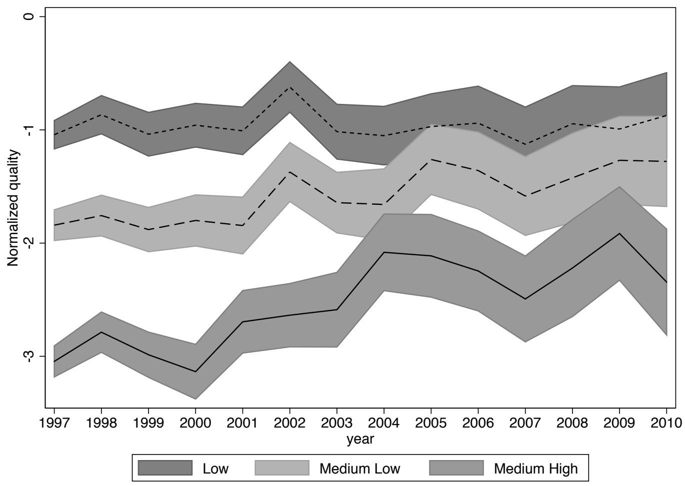

FIGURE 7: Low Price Varieties Upgrade their Quality over the Period

Notes: The figure reports the yearly average quality of French firms belonging to different price quartiles in 1997: Low, Medium Low and Medium High. 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

[27]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 to zero over the period.

[28]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 upgrade their quality in response to Chinese competition.

to upgrade the quality of their product. In order to isolate this quality response through a counterfactual experiment, we need to measure the impact of quality upgrading on the cost of the firm.

5.3 Supply Side Estimation Results

In section 4, we provide two relationships to estimate the quality response to a change in competition. First, the first order condition on quality governs the extent of this quality response through the relationship between the quality of a variety and its inverse average price-elasticity $\tilde{\alpha}^{-1}$. Second, the relationship between the marginal cost of production and the square of this inverse average price-elasticity also identifies the coefficient h that characterizes this quality response. These specifications rely on the quadratic effect of quality on marginal cost: as the product quality of a variety increases, the marginal cost of production rises increasingly. This convexity guarantees that firms choose a finite optimal level of quality.[29]

We present the results of this estimation in table 5. The first three columns show the regression of the quality measure on $\tilde{\alpha}^{-1}$. These regressions estimate $\frac{1}{2h}$ from which we can recover h. We report the OLS regression in column (1) as well as two 2SLS specifications in columns (2) and (3) that respectively use the average or initial characteristics of the variety to construct the instrument for $\tilde{\alpha}^{-1}$. All three specifications include firm-destination-hs6 and destination-year fixed effects such that the identification takes place between varieties across times. Columns (1)-(3) of table 5 validate our instrumental strategy: the OLS estimate is very large because endogenous quality choice generates spurious correlation between quality and inverse price elasticity. However, our instrumental strategy corrects for this endogeneity and estimates a much smaller relationship between price-elasticity and quality. Still, we find that firms facing an exogenous increase in their average own-price elasticity increase the quality of their product. Moreover, this estimated relationship identifies a value for the parameter h around 0.06.

To check the robustness of this estimate, we look at the relationship between marginal cost and the square of inverse average elasticity in columns (4)-(6). This relationship identifies $\frac{1}{4h}$ such that we can use this relationship to estimate h and quantify the impact of producing high quality products on marginal costs. These specifications display similar patterns: our instruments strongly impact the estimated coefficients and we find very consistent results across our instruments.

[29]To confirm that the relationship between marginal costs and quality is indeed quadratic, figure 13 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.

TABLE 5: Estimation results: supply side

	quality λ_{jdt}			$\log mc_{jdt}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\tilde{\alpha}^{-1}$	81.2***	8.50***	7.74**			
	(2.44)	(2.31)	(2.43)			
$(\tilde{\alpha}^{-1})^2$				29.2***	1.85***	1.27**
				(0.74)	(0.47)	(0.46)
$\hat{h}$		0.059	0.064		0.135	0.197
R^2	0.88			0.95		
FS F-stat		4878.1	7769.5		4072.1	7461.0
Instruments	.	Average	Initial	.	Average	Initial

Notes: 89 250 observations. Firm-level clustered standard errors between parentheses. All specifications include destination-year and firm-product-destination fixed effects. Significance levels: * p<0.05, ** p<0.01, *** p<0.011.

We do find larger estimates of h with that method: we obtain values around 0.15, relative to 0.06 when using the quality measure. However, given the standard errors around these estimates, they are not statistically different from each other and we will use a baseline value of 0.1 for the parameter h in our counterfactual exercise.[30]

These results confirm the quality response of French exporters when facing a change in the competitive environment. In the next section, we quantify the extent to which this quality response helped French firms mitigate the impact of the China shock.

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.

[30]A potential explanation for this difference could come from an impact of quality not only through marginal costs, but also adjustment costs. In that case, we would measure a smaller impact on marginal cost than quality cost, because marginal cost only captures one aspect of the additional cost of quality. However, capturing more complex effects of quality on the cost structure is not doable in our framework. Figures 15 and 16 in appendix B show that our counterfactual results are not sensitive to these different values of h.

We start by describing the counterfactual experiment and present the results in a simple case where French firms cannot change the quality of their products. Then, we move to a scenario where firms are allowed to adjust their quality and describe the impact of this additional margin of adjustment.

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 at this stage of the counterfactual experiment, we allow them to update their pricing strategy. In a scenario where China does not grow, we expect French firms to have a pricing strategy different from their actual 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.[31] 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.[32]

Figure 8 shows the unequal effect of the China shock. Firms at the bottom of

[31] We do not allow foreign countries to adjust their mark-ups since this would require using 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.

[32] We use the median effect because we see a broad dispersion across products and destinations. Figure 14 in appendix B provides the distribution of these effects for the logarithm of the market share.

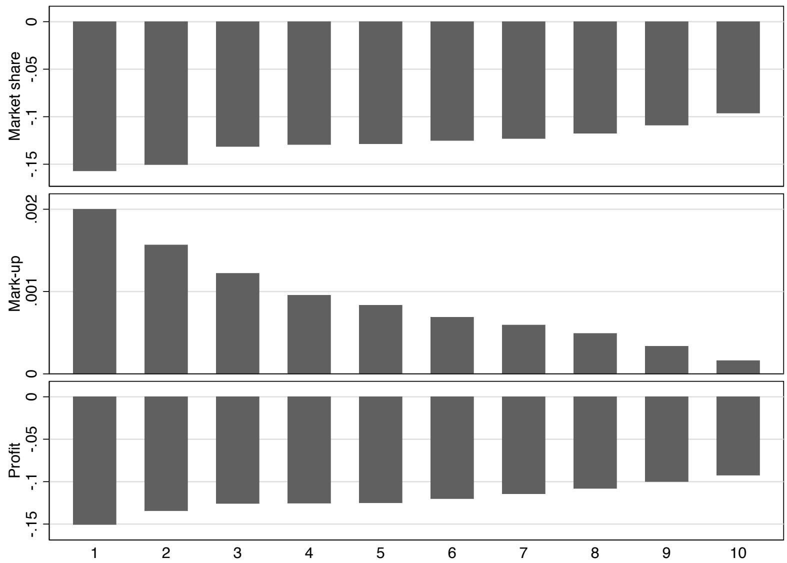

FIGURE 8: Effect of the China shock by price deciles (on French firms in 2010)

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.

the price distribution see their market shares decrease by 16%. On the contrary, firms at the top of the price distribution only experience a 9% 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 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 and mostly apply to firms most affected by Chinese competition, at the bottom of the price distribution: the median increase in mark-up for these firms is equal to 0.2%.

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.[33]

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.

6.2 Accounting for Quality Adjustment

The demand system estimated in the previous sections imply that firms may want to adjust their quality after a change in competition. In order to quantify this response in the context of the China shock, we now run our counterfactual allowing for endogenous quality adjustments. Once again, we implement our experiment by setting the prices and quality of Chinese producers to their pre-2001 levels. However, due to quality adjustments, we need to update the new quality, mark-ups and marginal costs of each French firms that describe the new equilibrium. In order to do so, we rely on three equations from the models: the pricing equation (8), the first order condition on quality (10) and the marginal cost function (6). From these three equations and the initial equilibrium objects $\left\{mk_{jdt}^{(0)}, mc_{jdt}^{(0)}, \lambda_{jdt}^{(0)}\right\}$, we can find the new equilibrium by iterating over the following set of equations:

$$
\begin{aligned}
mk_{jdt}^{(s)} &= 1 + \frac{\int \mathbb{P}_{jdt}^{(s-1)}(y,\nu)\,\omega_{jdt}(y,\nu)\,dyd\nu}{\int \exp(\alpha(y,\nu))\left(1-\mathbb{P}_{jdt}^{(s-1)}(y,\nu)\right)\ \mathbb{P}_{jdt}^{(s-1)}(y,\nu)\,\omega_{jdt}(y,\nu)\,dyd\nu} \\
\lambda_{jdt}^{(s)} &= \lambda_{jdt}^{(0)} + \frac{1}{2h}\left(\left(\tilde{\alpha}^{-1}\right)^{(s-1)} - \left(\tilde{\alpha}^{-1}\right)^{(0)}\right) \\
mc_{jdt}^{(s)} &= mc_{jdt}^{(0)} + \left(\tilde{\alpha}^{-1}\right)^{(0)}\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right) + h\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right)^2 \\
\mathbb{P}_{jdt}^{(s)}(y,\nu) &= \frac{\exp\left(\delta_{jdt}^{(s)} + \mu_{jdt}^{(s)}(y,\nu)\right)}{1+\sum_{j\in F}\exp\left(\delta_{jdt}^{(s)} + \mu_{jdt}^{(s)}(y,\nu)\right) + \sum_{j\notin F}\exp\left(\delta_{jdt} + \mu_{jdt}(y,\nu)\right)} \\
\left(\tilde{\alpha}^{-1}\right)^{(s)} &= \frac{\int \mathbb{P}_{jdt}^{(s)}(y,\nu)\left(1-\mathbb{P}_{jdt}^{(s)}(y,\nu)\right)\ \omega_{jdt}(y,\nu)\,dyd\nu}{\int \exp(\alpha(y,\nu))\,\mathbb{P}_{jdt}^{(s)}(y,\nu)\left(1-\mathbb{P}_{jdt}^{(s)}(y,\nu)\right)\ \omega_{jdt}(y,\nu)\,dyd\nu}
\end{aligned}
$$

with $\delta_{jdt}^{(s)} = x_{jt}\beta + \lambda_{jdt}^{(s)}$ and $\mu_{ijdt}^{(s)} = x_{jt}(\beta_i - \beta) - \exp(\alpha_i)(\ln p_{jdt}^{(s)} - \ln p_{0dt})$.

We iterate the conditions until convergence to obtain the equilibrium prices, quality and marginal costs of all French firms under this new environment. Once again, we keep constant the characteristics of foreign countries since the esti-

[33] 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.

mation of their mark-ups, and marginal costs, are not consistent. We can then compare the effect of the China shock on market shares, profit and mark-ups in two scenarios: one in which French firms maintained their quality, and one in which they could endogenously change the quality of their product.

In figure 9, we compare the log-change in market share, mark-up, profit and quality of French firms in different price deciles. We report the outcomes without quality change from the previous paragraphs for comparison purposes. 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 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.

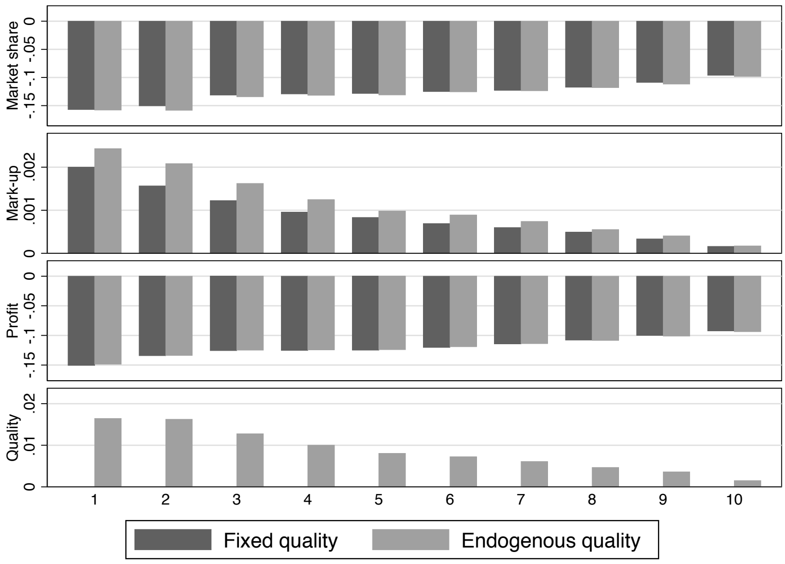

Figure 9: Effect of the China shock and the quality response

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.

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. The cost of quality upgrading is large enough that firms still suffer significant losses despite the possibility of upgrading their products.[34] It indicates that this mechanism only offers limited relief for firms aiming at mitigating the adverse effects of low-cost countries competition.

6.3 Replicating the Heterogeneous Effect of the China Shock

To conclude the description of our counterfactual experiment, we asses the extent to which the 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, but allow characteristics of foreign producers to vary over time. In other words, we quantify the evolution of French market shares that is only due to the change in the competitive environment, holding constant productivity and quality of French exporters. 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. Therefore, it confirms that the rise of competition from low-cost countries can quantitatively explain the diverging trajectories of low-price and high-price firms in foreign markets.

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. 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 more than 50% 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.

[34] We verify in figures 15 and 16 in appendix B that this conclusion is robust to using different value for h, the parameter that disciplines this quality response.

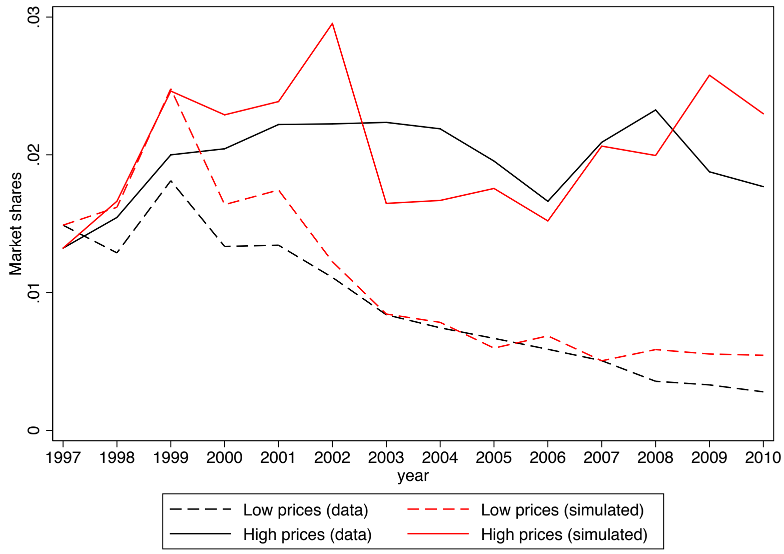

FIGURE 10: Role of the change in competition.

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

Overall, these results underline the importance of considering realistic substitution patterns to understand the impact of foreign competition on firm performance and decisions. It also highlights that policies aiming at escaping low-cost competition through quality upgrading or innovation need to account for the large adjustment costs that these investments entail.

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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 6 summarizes the classification of countries as used in the paper.

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

Table 6: 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			

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

[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.

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 faced by final consumers. To this end, we convert unit values to the importer's currency. We also inflate unit values by the applied tariffs, described below, and an ad valorem transportation cost. These transportations costs are 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.

Tariffs data We use tariffs data from the Market Access Map (MAcMap) dataset provided by the CEPII. In its public version, it provides information about the bilateral tariffs rates applied at the HS2 level. For our application, we use tariffs applied to the HS2 code 64: "Footwear; gaiters and the like; Parts of such articles". Since the dataset only provides applied tariffs for the year 2001, 2004 and 2007, we apply the 2001 tariffs to the 1997-2002 period, the 2004 tariffs to the 2003-2005 period and the 2007 tariffs to the 2006-2010 period.

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:

$$\ln p_{fdpt} = FE_{dpt} + u_{fdpt}$$
$$\ln p_{fdpt} = FE_{fp} + FE_t + v_{fdpt}$$

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 7 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 7 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 7: Selection of product codes

Product code	Description	Included	Characteristics Boot	Top leather	Sole leather	Top fabric
640110	Waterproof footwear incorporating a protective metal toe-cap	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

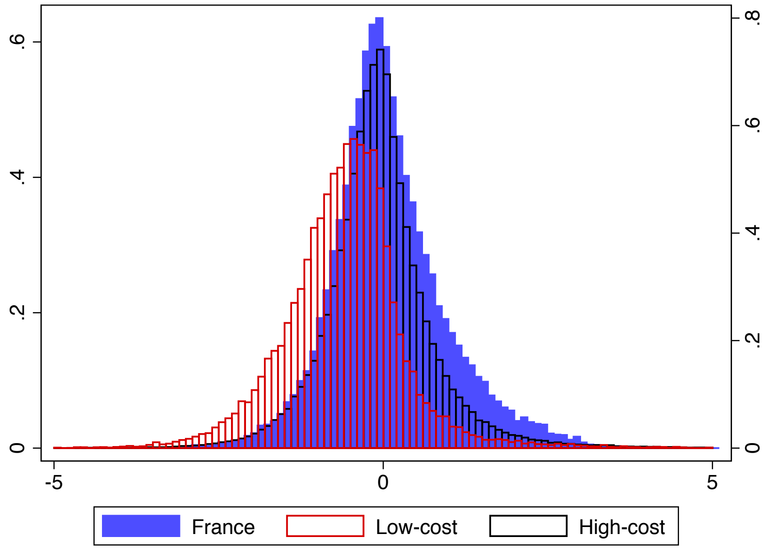

FIGURE 11: Distribution of Export prices

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.

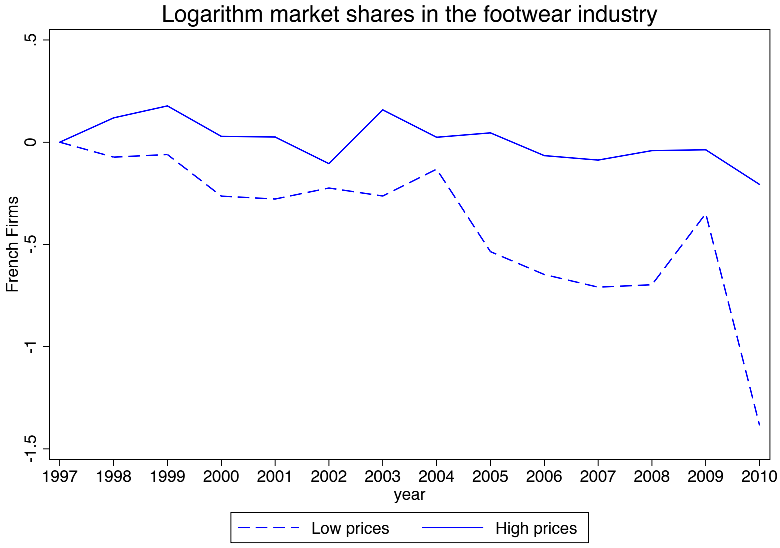

FIGURE 12: low-cost French shoe producers have suffered more than expensive shoe producers.

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.*

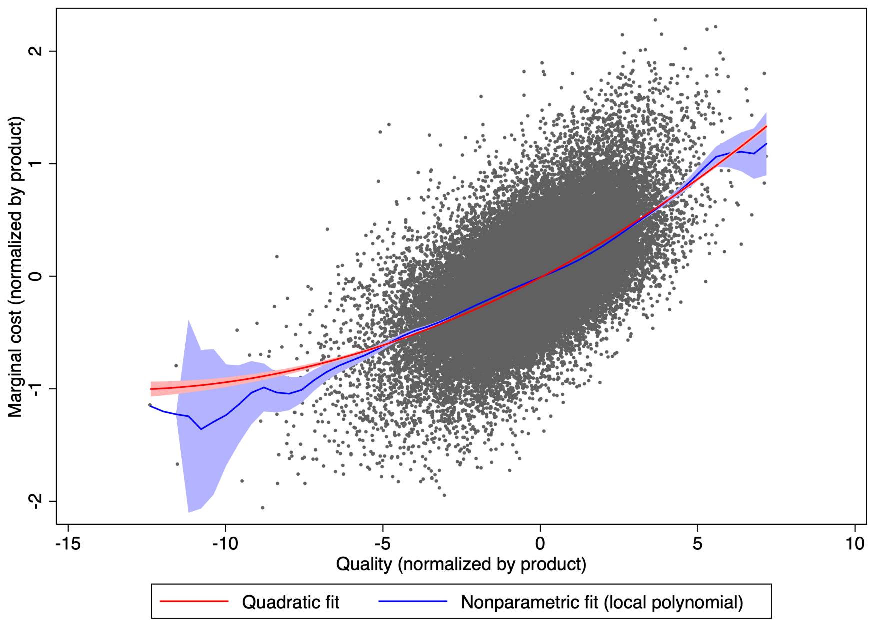

FIGURE 13: Relationship between marginal cost and product quality

Notes: Both measures are normalized within destination-year group and within firm-product-destination group.

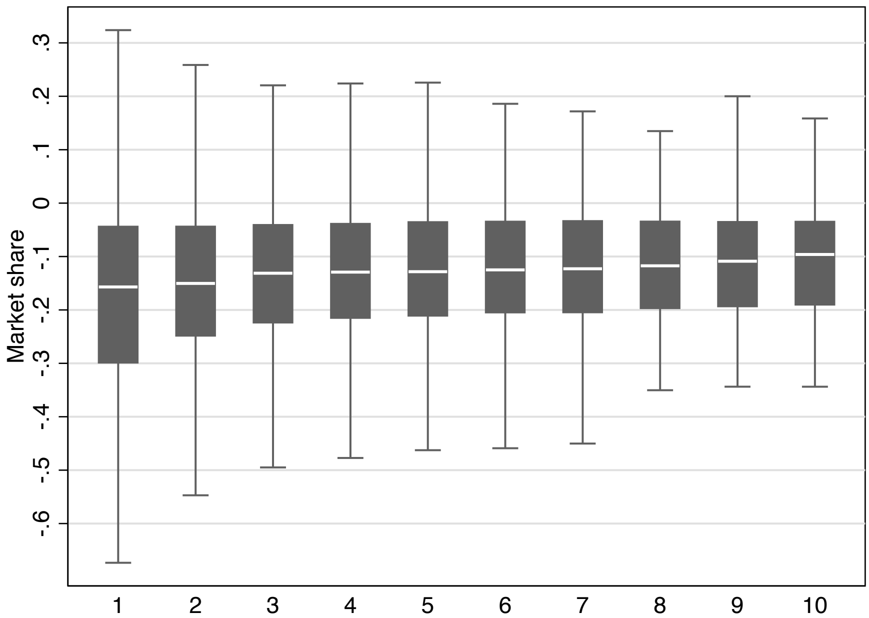

FIGURE 14: Distribution of the effect of the China shock on market shares by price deciles (on French firms in 2010)

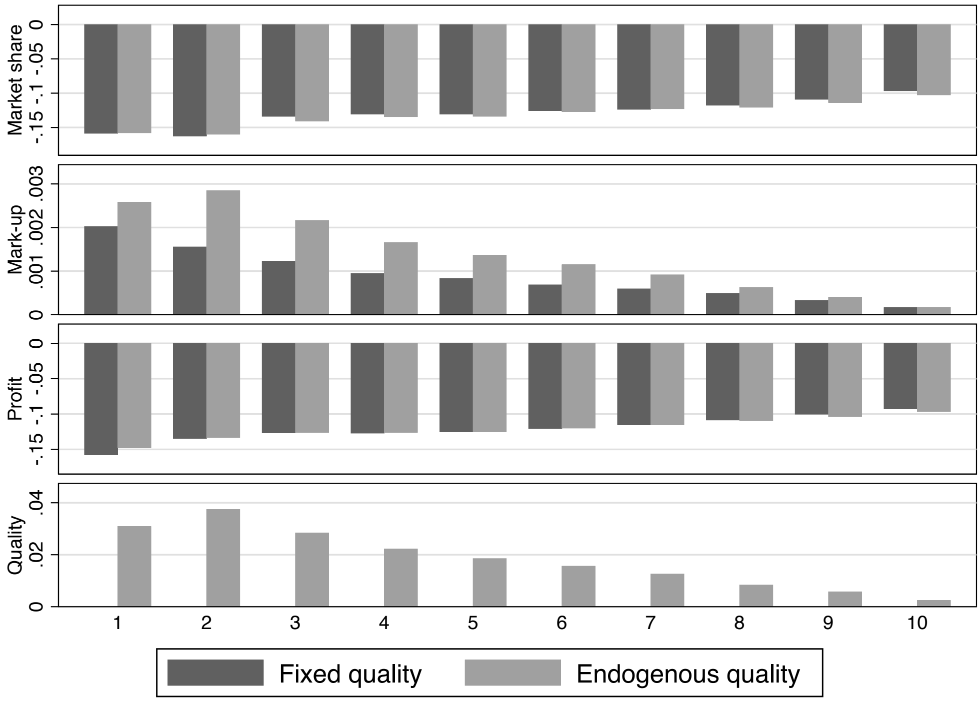

FIGURE 15: Effect of the China shock and the quality response with $h = 0.06$

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.

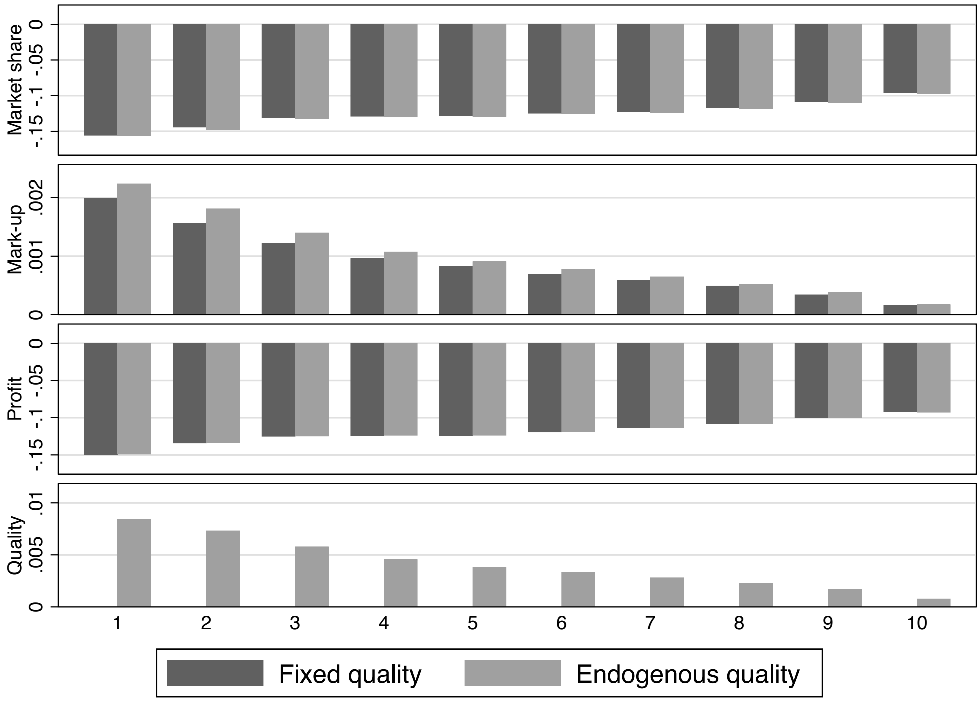

FIGURE 16: Effect of the China shock and the quality response with $h = 0.19$

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.