Foreign Competition along the Quality Ladder*

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November 2019

Abstract

We propose an empirical model of trade with random-coefficients demand and endogenous product quality. Unlike commonly used demand systems (e.g. CES, nested logit), this model generates rich substitution patterns across producers and implies an "escape-competition" effect: in response to low-cost competition, firms may upgrade their product quality to reach segments of the market that are less exposed. The estimation, using trade data from French shoe exporters, reveals significant heterogeneity in consumer preferences based on income and unobservable characteristics. Using the estimated model to quantify the unequal impact of the "China shock", we find that Chinese competition was twice more damaging to French firms at the bottom of the price distribution, and that quality upgrading did little to mitigate the impact of the shock.

*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, the Bank of Italy, ETSG 2017, EIIT 2017, SED 2018, RMET 2019 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 costs 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 generate an "escape-competition" effect: firms will have incentives to upgrade their product quality as low-cost competition increases the relative profit from high-quality goods. Therefore, this model not only identifies more precisely the impacts of low-cost competition, it also implies quality choice as a possible margin of adjustment, a feature absent in CES frameworks. Our empirical strategy measures the cost of producing higher quality good and shows that this quality response did little to mitigate the effects 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 more affected by competing firms that resemble them.

Based on this evidence, we develop an empirical model in which consumers have heterogeneous preferences and firms choose their optimal product quality. On the demand side, we follow Berry, Levinsohn, and Pakes (1995, hereafter BLP) 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 unobservable characteristics. We aggregate these preferences using the income distribution observed in these foreign markets as well as distributional assumptions on the unobservables. A first implication of this heterogeneity is to generate heterogeneous markups across producers: firms with high quality products serve consumers that are relatively inelastic. As a conse-

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

quence, these high-quality firms charge higher markups relative to low-quality firms. Moreover, these heterogeneous preferences also create substitution patterns across varieties that depend on their proximity in the product space. For instance, low-cost varieties are 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. Assuming convexity in the cost of producing quality, 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, because it appeals mostly to elastic consumers, will imply a reallocation of French sales toward inelastic consumers, encouraging French firms to produce higher quality products.

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 its evolution over the period is similar to other manufacturing sectors also exposed to the rise of low-cost competition. We estimate the demand system separately from the supply side, 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 exchange rates on firms' imports to instrument firm-level prices. Second, the use of international trade data facilitates the identification of random coefficients by providing large variation across destinations in income distributions and in the cross-elasticity between low and high-cost varieties. Therefore, with the same data requirements as existing papers estimating demand in international trade, we can capture heterogeneity in preferences from variations in income distributions across destination markets.

The demand estimation results confirm the existence of heterogeneous consumers. We find that the heterogeneity in price-elasticity is particularly related to consumers 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 10 to more than 100 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. Some firms have a cross-elasticity with Chinese products close to zero, while some others records a cross-elasticity with China larger than one, indicating a strong substitutability

[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.

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 also display heterogeneity in their preference for product characteristics other than prices, as well as in their preference for French goods. This result implies stronger substitution patterns between French firms and varieties that share the same characteristics.

The estimation of the demand system delivers a series of firm-level estimates, such as markup, product quality and average price elasticity, from which we are able to estimate the supply side of the model. From the estimated markups and observed prices, we can infer the marginal cost of a variety and estimate how these costs vary with product quality. However, estimating the relationship between marginal costs and quality presents identification challenges: any change in quality by the firm is likely to be voluntary, and could be triggered by a change in the cost of producing quality. Therefore, the comovement between quality and marginal costs is likely to be weakened by endogeneity issues. Fortunately, our model delivers an exogenous instrument for quality change: as the competitive environment changes, the set of consumers faced by a French firm evolves, modifying the optimal quality the firm should produce. For instance, French firms face higher incentives to produce high-quality products as low-cost producers gain market shares. Therefore, we construct an instrument based on exogenous changes in competition. As firms adjust their product quality in response to these exogenous factors, we can measure the associated changes in marginal costs, which consistently identify the cost of producing higher quality products.

Using outcomes from the demand estimation, 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, we implement our instrumental variable strategy to structurally estimate the cost of quality upgrading. We show that both quality and marginal costs respond to exogenous changes, due to competition, in the average price elasticity: as competition reallocates consumers between varieties, firms losing price-elastic consumers for inelastic consumers tend to optimally increase their quality and their marginal cost. Therefore, we are able to quantify the convexity of the cost of producing quality, which allows us to discipline the extent to which firms will use quality upgrading to escape low-cost competition.

Finally, as a natural application of our model, we characterize the competition 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 look at the impact on French firms in 1997, of raising Chinese exporters' characteristics to their post-2007 levels. 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 roughly twice larger at the bottom of the price distribution relative to the top: increase in Chinese competition generates a median 22 percent loss in market shares for the first decile in the price distribution. Meanwhile, firms in the highest price decile record a median 12 percent loss. Moreover, we find that the ability of firms to upgrade the quality of their product did little to help them mitigate this shock. Allowing firms to upgrade quality reduces the impact of Chinese competition by a small amount across price deciles, due to the large costs associated with quality upgrading.

Our work relates to the literature estimating firm 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 firms' 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 to study how vertical differentiation shapes the firm-level impact of trade.

Moreover, we add to the many studies linking trade and quality decisions. Amiti and Khandelwal (2013) documents the quality response to import competition using country-level data. Different channels have been documented to explain the relationship between trade and quality, 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 firms' 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 due to 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. Moreover, Coşar et al. (2018) estimate mixed preferences using micro trade data when decomposing the origin of the home market effect. In contrast to these papers, we use micro data to estimate realistic substitution patterns at the firm level, 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

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

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 model and section 5 describes the results of this estimation. Finally, we quantify the impact of Chinese competition in section 6, and conclude in section 7.

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 describe the datasets used in the paper, and then document the heterogeneous effects of foreign competition across 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 the 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 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 uses weights (in tons) as quantities. 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

[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.

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 B 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 convert unit values into the importer's currency and 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. As a result, we obtain import prices which reflect the final price 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 combines 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 firm-level French exports and foreign competition.

2.2 Stylized Facts

In this section, we show that the patterns of substitution between firms in foreign markets are related to vertical differentiation. More precisely, we show that French exporters located at 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. To this end, 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. Specifically, we project the logarithm of the unit value of each French firm before 2001 on a set of firm-product-destination and product-destination-year fixed effects:[8]

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

so that the fixed effect γ_{fpd} measures the position of triplet fpd in the price distribution. From

[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 B for details.

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

this measure, we construct the price quartiles PQ_{fpd}, which correspond to the quartile rank of γ_{fpd} in the distribution of destination pd.

Having classified French exporters according to their position in the price distribution, we now investigate how they perform in response to changes in foreign competition from low-cost countries. For each destination market pdt, we compute the variable MSL_{dpt}, the market share of exports originating from low-cost countries,[9] and estimate how individual exporters are differently affected by the change in this market share. Specifically, we estimate the following regression:

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

where Y_{fdpt} is a measure of export performance, either the logarithm of export values or a dummy for survival. We interact the market share MSL_{dpt} with a full set of dummies for the price quartile of the firm-product in that destination PQ_{fpd}. As such, parameters δ_q measure the relative impact of low-cost competition on the export performance of French firms across price levels. Moreover, we include two sets of fixed effects in the regression. 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. In summary, this specification captures the relative change in the export performance of French firms across different price segments, when import competition from low-cost countries increases.

We report the results of these regressions in table 1.[10] In column (1), we only include a market-year fixed effect FE_{dpt}, such that the identification comes from relative export values between exporters in the same destination market. The coefficients related to the interaction terms are all positive and monotonically increasing, which implies that high price firms have relatively larger export values in 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-variety identification of the parameters. Once again, interaction coefficients are significantly larger than zero, which means that when the market share of low-cost countries goes up in a market, the market shares of high-price firms decrease relatively less than the ones 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 1.5 to 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

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

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

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***	.	0.010***	.
	(0.01)		(0.0008)	
3rd price quartile	-0.30***	.	0.019***	.
	(0.01)		(0.0008)	
4th price quartile	-0.26***	.	0.0012	.
	(0.010)		(0.0007)	
Low-cost penetration				
× 2nd price quartile	0.58***	0.14***	0.033***	0.065***
	(0.04)	(0.04)	(0.004)	(0.009)
× 3rd price quartile	0.84***	0.20***	0.038***	0.090***
	(0.04)	(0.04)	(0.004)	(0.008)
× 4th price quartile	1.17***	0.15***	0.059***	0.11***
	(0.04)	(0.04)	(0.003)	(0.008)
N	6 279 484	6 146 729	6 046 452	5 926 317
R^2	0.45	0.87	0.14	0.39
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<0.01.

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 decreases by one point relative to high-price firms.

A potential explanation for these results could be that low-price firms are less resilient to any type of competition, and not specifically to low-cost competition. To show that this pattern is specific to competition from low-cost producers, we rerun 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 in the price distribution, display stronger substitution patterns. Figure 12 in the appendix E supports this hypothesis: it shows that prices of varieties from developing countries are closer to those of low-price French exporters than those of 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

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

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

Dependent variable:	*log export* (1)	(2)	*Survival* (3)	(4)
2nd price quartile	0.090***	.	0.028***	.
	(0.02)		(0.002)	
3rd price quartile	0.051**	.	0.038***	.
	(0.02)		(0.002)	
4th price quartile	0.25***	.	0.041***	.
	(0.02)		(0.002)	
High-cost penetration				
× 2nd price quartile	-0.34***	-0.059	-0.021***	-0.037***
	(0.03)	(0.03)	(0.003)	(0.007)
× 3rd price quartile	-0.37***	0.033	-0.022***	-0.053***
	(0.03)	(0.03)	(0.003)	(0.006)
× 4th price quartile	-0.54***	0.051	-0.048***	-0.057***
	(0.03)	(0.03)	(0.003)	(0.006)
N	6 279 484	6 146 729	6 046 452	5 926 317
R^2	0.44	0.87	0.14	0.39
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<0.05, *** p<0.01.

can not only account for these patterns, but also generate realistic implications for the markup distribution, and for the endogenous quality response of firms to competition changes.

3 Model

We present an empirical model of trade with realistic substitution patterns between varieties and endogenous product quality. Following BLP (1995), the demand system features heterogeneous consumers which differ in their preferences over product characteristics. As a consequence, products that share similar characteristics or are close in the product space, are stronger substitutes. In addition to capturing complex substitution patterns, the presence of heterogeneous consumers generates further desirable features: the model predicts variable markups 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 who consume at different time periods t. In each destination, each consumer

i chooses among the set of foreign varieties available, denoted Ω_{dt}, 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. To facilitate the exposition of the model, we ignore the subscripts d and t, even though our empirical application is implemented in many destination countries and many periods.

The utility derived by consumer i from consuming variety j is

$$u_{ij} = q_{ij} \exp\left(\frac{x_j\beta_i + \lambda_j + \varepsilon_{ij}}{\exp(\alpha_i)}\right),$$

where q_{ij} is the quantity of variety j consumed by i and x_j is a K-dimensional vector of observable product characteristics. Moreover, λ_j is the quality of a variety j, which contains any unobservable characteristic that raises the valuation of variety j from the point of view of all consumers. Finally, ε_{ij} is an idiosyncratic shock in consumer i's valuation of variety j. In this utility function, β_i describes the valuation of characteristics x_j by consumer i, while 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 $q_{ij} = \frac{e(y_i)}{p_j}$ physical units, with $e(y)$ the budget allocated by a consumer with log-income y to the consumption of shoes, and p_j the unit price of variety j.[12] 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

$$V_{ij} = x_j\beta_i - \exp(\alpha_i)\ln p_j + \lambda_j + \varepsilon_{ij}.$$

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 - λ_0 - to zero. Consequently, the measured quality of foreign varieties should be interpreted in deviation to the quality of the outside good. In the empirical application, we will consider the domestic variety as outside good.[13] Nevertheless, we do not set the price of the outside good to zero: such normalization would impose strong assumptions on the substitution patterns between the outside good and other varieties.

Assuming that the idiosyncratic shock ε_{ij} follows a Type I extreme-value distribution, the probability that consumer i buys variety j is

$$\mathbb{P}_{ij} = \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{j'\in\Omega} \exp(\delta_{j'} + \mu_{ij'})}, \tag{2}$$

[12]Random coefficient discrete choice models usually assume that consumers purchase a single unit of the differentiated good. By contrast, our assumption that consumers purchase continuous quantities follows Anderson, De Palma, and Thisse (1992) and delivers the appealing feature that individual demand depends on log prices (rather than prices). Recent trade papers with random coefficients such as Adao, Costinot, and Donaldson (2017) or Heins (2016) use a similar specification.

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

with $\delta_j \equiv x_j\beta + \lambda_j$ and $\mu_{ij} \equiv x_j(\beta_i - \beta) - \exp(\alpha_i)(\ln p_j - \ln p_0)$. This notation allows us to separate the components of the indirect utility that are common across consumers, δ_j, from the ones that are consumer-specific, μ_{ij}.[14]

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 market. Since consumers are heterogeneous in their preferences, and therefore decisions, we obtain the aggregate demand by integrating these individual decisions over the consumers distribution. Specifically, we assume that these preferences are distributed as follows

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi y_i + \Sigma \nu_i, \qquad y_i \sim F_y(y),\, \nu_i \sim F_\nu(\nu) \tag{3}$$

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. Equation (3) implies that the random coefficients depend linearly on the log-income of the consumer y_i and a vector of random shocks ν_i. In the empirical application, the distribution of y_i, F_y, will follow a normal distribution based on the income distribution observed in each destination market d. For each country, we translate information on the GDP per capita and Gini indices to first and second moments of a log-normal distribution.[15] Moreover, we assume that each element of vector ν_i follows an independent standard normal distribution. In summary, through equation (3) we allow consumer preferences for prices and other characteristics to vary according to their income and unobserved source of variations.

Having specified the distribution of preferences, we can now derive an expression of the aggregate demand for variety j. Equation (3) 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 i to pick a variety j as a function of y_i and ν_i:

$$\mathbb{P}_j(y,\nu) = \frac{\exp\left(\delta_j + \mu_j(y,\nu)\right)}{1 + \sum_{j' \in \Omega} \exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)}\,. \tag{4}$$

It follows that the sales of variety j in a given market are

$$r_j = \int e(y) \frac{\exp\left(\delta_j + \mu_j(y,\nu)\right)}{1 + \sum_{j' \in \Omega} \exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)} F_y(y) F_\nu(\nu)\, dy\, d\nu \tag{5}$$

and the respective market share (in revenue) is

$$s_j \equiv \frac{r_j}{\sum_{j' \in \Omega} r_{j'}} = \int \mathbb{P}_j(y,\nu)\, \omega^{(1)}(y,\nu)\, dy\, d\nu\,, \tag{6}$$

with $\omega^{(1)}(y,\nu) \equiv \frac{e(y)\,F_y(y)\,F_\nu(\nu)}{\int e(y)\,F_y(y)\,F_\nu(\nu)\,dy\,d\nu}$. The revenue market share of variety j is the probability

[14] Note that we use an exponential transformation to guarantee that the price-elasticity, $-\exp(\alpha_i)$, is negative for all consumers. Therefore, and unlike in BLP (1995), the mean value of α_i is not contained in the common utility term δ_j.

[15] See appendix B for details.

that a consumer picks the variety, averaged across consumers, and weighted by the budget of each consumer.

3.2 Supply side

Having described demand fundamentals, we can now turn to the supply side. Importantly, the specification of this supply side will not play a role in the demand estimation: because prices are observed in the data, the estimation of the demand system does not rely on assumptions made about the cost function of the firm. Nevertheless, specifying the supply side will be crucial when implementing the counterfactual experiments in the last section of the paper. In these experiments, we quantify the endogenous quality response of firms to a change in competition, which requires to specify and estimate the cost of producing higher quality products.

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

$$\ln c_j = x_j \rho + \eta_j \lambda_j + h\lambda_j^2 + \varphi_j. \tag{7}$$

Product characteristics x_j enter this cost function through the vector of parameters ρ, while quality affects the marginal cost function through an idiosyncratic quality-elasticity of costs η_j and a quadratic term $h\lambda_j^2$. Two main characteristics are worth noting in this cost function. First, we allow for two important sources of heterogeneity across varieties: firms differ in their ability to produce quality, through the parameter η_j, and their physical productivity with parameter φ_j. This heterogeneity allows us to rationalize any observed price set by a firm, by adjusting the productivity term φ_j, and to explain any measured quality level λ_j through the idiosyncratic cost of producing quality η_j. While we do not specify the distribution of these sources of heterogeneity, we will be able to recover their values from the estimation procedure.

A second important characteristic of this function is the convexity in the cost of producing quality, captured by the parameter h. This convexity will be crucial to ensure that firms choose a finite level of quality at the equilibrium.[16] Moreover, this degree of convexity will discipline the extent to which firms are willing to adjust their quality in response to a competition shock. As such, the value of the parameter h will quantify how quality adjustments help firms mitigate the adverse consequences of a negative competition shock.[17]

3.3 Firm's Problem

Having described demand and supply fundamentals, we can now turn to the problem of the firm. In each market, a firm sets price and product quality to maximize its profit function. Assuming constant marginal cost of production, the profit function of a firm f consists of the

[16]See Kugler and Verhoogen (2012) for a similar convexity requirement on the cost of producing quality.

[17]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 ultimately find 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.

sum of individual profits from each of its variety j. Denoting F the set of variety owned by firm f, the firm's profit function is:

$$\Pi_f = \sum_{j \in F} \pi_j(p_j, \lambda_j) = \sum_{j \in F} r_j(p_j, \lambda_j) \left(1 - \frac{c_j(\lambda_j)}{p_j}\right) . \tag{8}$$

This notation specifically emphasizes the two sets of choice variables of a firm, in each market: the price and product quality of each of their variety j. We assume that both decisions are made simultaneously by solving their respective first order conditions on profit.

Optimal pricing Firms choose each price p_j to maximize the sum of the profits made with each variety. Taking into account cannibalization across varieties, the set of first order conditions for each price p_j of firm f is the following:

$$\sum_{j' \in F} \frac{\partial \pi_{j'}}{\partial p_j} = 0 , \quad \forall j \in F \qquad \Leftrightarrow \qquad r_j \frac{c_j}{p_j^2} + \sum_{j' \in F} \frac{\partial r_{j'}}{\partial p_j} \left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0 , \quad \forall j \in F$$

and can be rewritten in vectorized form, by stacking up the first order conditions of all varieties in a market:

$$M - \Delta(1 - M) = 0 \tag{9}$$

where M is the vector of the inverse multiplicative markups, $M_j \equiv \frac{c_j}{p_j}$, and Δ the matrix defined as

$$\Delta_{j,j'} = \begin{cases} \int (1 - \mathbb{P}_j(y,\nu)) \, \exp(\alpha(y,\nu)) \, \omega_j^{(2)}(y,\nu) \, dy d\nu & \text{if } j = j', \\ - \int \mathbb{P}_{j'}(y,\nu) \, \exp(\alpha(y,\nu)) \, \omega_j^{(2)}(y,\nu) \, dy d\nu & \text{if } j \text{ and } j' \text{ belong to the same firm,} \\ 0 & \text{otherwise,} \end{cases}$$

with $\omega_j^{(2)}(y,\nu) \equiv \frac{e(y)\mathbb{P}_j(y,\nu)F_y(y)F_\nu(\nu)}{\int e(y)\mathbb{P}_j(y,\nu)F_y(y)F_\nu(\nu)dyd\nu}$ the share of consumers with characteristics y and ν in the revenues of the firm.[18] In the case of a single-product firm, the firm only cares about the diagonal term of the matrix Δ, so that the optimal pricing rule becomes:

$$\frac{p_j}{c_j} = 1 + \frac{1}{\Delta_{j,j}} = 1 + \frac{1}{\int (1 - \mathbb{P}_j(y,\nu)) \, \exp(\alpha(y,\nu)) \, \omega_j^{(2)}(y,\nu) \, dy d\nu} , \tag{10}$$

Intuitively, the markup charged by a firm is an inverse function of the price elasticity of the average consumer it serves. Therefore, firms producing goods that are more appealing to rich consumers set higher markups since their average consumer is less price-sensitive.

This result highlights a desirable feature of a model with random coefficients: markups charged by a firm are increasing with the quality of its products. By contrast, in models with a representative consumer, all firms charge the same markup because they all face the same price-elasticity for their products. We can see that, in the absence of heterogeneity across consumers, we obtain the usual pricing rule from oligopolistic competition: $\frac{p_j}{c_j} = 1 + \frac{1}{(1-\mathbb{P}_j)\exp(\alpha)}$. In this context, markups decrease with the price elasticity of the representative consumer and increase with the market share of the firm. Therefore, while most trade models can only explain the

[18] See appendix A for details on the derivations.

correlation between prices and quality by the higher cost of quality, our framework can explain price dispersion from markups variations.

Optimal quality Similarly to prices, firms choose the quality of their products to maximize their profits. Higher quality leads to an increase in the sales of a firm, conditional on prices, but also raises the marginal cost of production. Therefore, firms trade-off between supplying an appealing product or an affordable product so that the optimal quality chosen by the firm directly depends on the cost of producing high quality, as well as on the consumers' price-elasticity: price-elastic consumers are less willing to pay higher prices to purchase higher quality goods. To highlight the role of these two objects, we write the firm's first order condition with respect to quality as follows:

$$\sum_{j'\in F} \frac{\partial \pi_{j'}}{\partial \lambda_j} = 0\,, \quad \forall j \in F \qquad \Leftrightarrow \quad -\frac{r_j}{p_j}\frac{\partial c_j}{\partial \lambda_j} + \sum_{j'\in f} \frac{\partial r_{j'}}{\partial \lambda_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0\,, \quad \forall j \in F$$
$$\Leftrightarrow \quad \frac{\partial \ln c_j}{\partial \lambda_j} = \frac{G_{(j)}(1-M)}{\Delta_{(j)}(1-M)}\,, \quad \forall j \in F \tag{11}$$

where G is defined as

$$G_{j,j'} = \begin{cases} \int (1-\mathbb{P}_j(y,\nu))\,\omega_j^{(2)}(y,\nu)\,dyd\nu & \text{if } j = j', \\ -\int \mathbb{P}_{j'}(y,\nu)\,\omega_j^{(2)}(y,\nu)\,dyd\nu & \text{if } j \text{ and } j' \text{ belong to the same firm,} \\ 0 & \text{otherwise,} \end{cases}$$

and $\Delta_{(j)}$ and $G_{(j)}$ respectively denote the j-th row of Δ and G.[19] Given our specification of the marginal costs of production in equation (7), the optimal quality can be written

$$\lambda_j^* = \frac{1}{2h}\left(\tilde{\alpha}_j^{-1} - \eta_j\right) \quad \text{with} \quad \tilde{\alpha}_j \equiv \frac{\Delta_{(j)}(1-M)}{G_{(j)}(1-M)}. \tag{12}$$

In order to obtain a more intuitive understanding of the role of $\tilde{\alpha}_j$ in this optimal quality, it is helpful to consider the case of a single-product firm. In this case, $\tilde{\alpha}_j$ equals the weighted average price elasticity of variety j's consumers

$$\tilde{\alpha}_j = \int \exp(\alpha(y,\nu))\,\omega_j^{(3)}(y,\nu)dy\,d\nu,$$

with $\omega_j^{(3)}(y,\nu) \equiv \frac{e(y)(1-\mathbb{P}_j(y,\nu))\mathbb{P}_j(y,\nu)F_y(y)F_\nu(\nu)}{\int e(y)(1-\mathbb{P}_j(y,\nu))\mathbb{P}_j(y,\nu)F_y(y)F_\nu(\nu)dyd\nu}$. This representation helps us summarize the determinants of firm product quality in expression (12). First, the optimal quality set by a firm depends on the elasticity of its costs to quality: firms with a small η_j 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 inverse of the price-elasticities of consumers the firm faces, through variable $\tilde{\alpha}_j$. When a firm serves consumers with a low price-elasticity, this firm is willing to increase costs through quality upgrading, because its consumers are relatively insensitive to high prices. Therefore, the lower the average price-elasticity of their consumers, $\tilde{\alpha}_j$, the more firms invest in quality.

[19] See appendix A for details on the derivations.

Moreover, when the competitive environment changes, consumers will adjust their purchasing decisions, modifying 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. Importantly, 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 consumers and leaves untouched firms' optimal quality.

Finally, equation (12) 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. As such, it will play a key role in shaping the results of the counterfactual experiments in section 6. In the 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 the relationship between marginal cost and quality.

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 model: the demand side, along with the set of instruments used to identify our demand system, and the supply side that aims at estimating the cost of quality upgrading. Appendices B and C respectively detail the data construction and the estimation.

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 categories correspond to regular shoes made of common materials and exclude articles such as soccer shoes, ski boots, waterproof shoes or shoe parts.[20]

We implement our estimation strategy using the footwear industry 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 B provides details regarding the creation of product characteristics.[21]

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

[20]The list of included and excluded product codes is reported in table 7 in appendix B.

[21]Table 10 in appendix E shows that we obtain very similar estimates when using product category dummies instead of these characteristics. However, our baseline specification will use product characteristics to limit the number of random coefficients in the estimation.

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 1 provides evidence of these patterns. As the market share of Chinese producers rose, the market share of affordable French shoes dropped. In the meantime, high-price French shoes were able to maintain, and even slightly gain market shares.

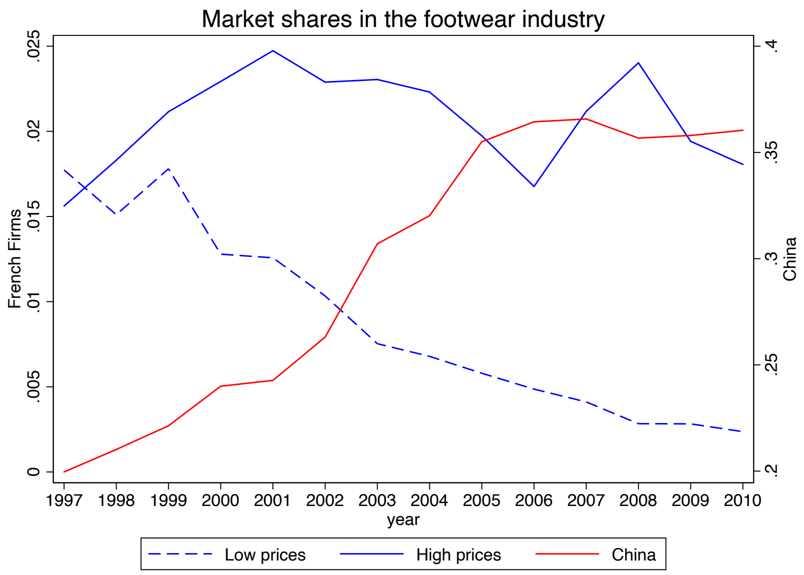

FIGURE 1: Chinese competition Hits Cheap Shoes Harder

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

To portray a more comprehensive picture of the global changes at play in the footwear industry, we look at the change over time of the distribution of shoe prices. In figure 2, we report for each year from 1997 to 2010, the distribution of French and low-cost country prices, weighted by their relative 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 a heterogeneous impact of low-cost competition along the price dimension.

Estimation sample The estimation procedure requires the market share and prices of all varieties within a specific market. In our context, we define a market as a destination country - year pair,[22] and a variety as the combination of an eight-digit product category and a producer. Because we combine micro level data from France and aggregate data from other countries, a producer can be a French firm or a foreign country.[23] Before taking the model to the data,

[22]We specifically use 38 countries from the WIOD database, dropping France and Luxembourg from the initial list of 40 countries included in the dataset. See table 6 in appendix B for details.

[23]We discuss the identification challenges created by this discrepancy in the next subsection.

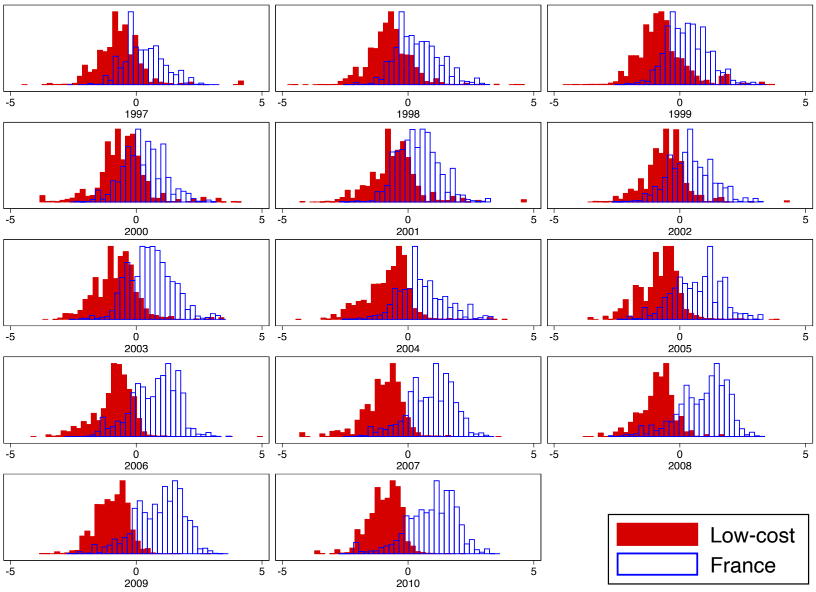

FIGURE 2: The price of French shoes diverge from low-cost competition

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.

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, and correct extreme prices from other countries' exports.[24] This cleaning procedure leaves us with 193 931 observations, including 103 633 from French producers representing 98.5% of total French shoe exports. Therefore, our cleaning procedure eliminates anomalous observations but maintains the very large majority of French exports. In table 3, we report summary statistics for the 2 415 distinct French firms that are part of the sample.[25] 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 percent, while the largest market share in the sample for a French firm is 1.5 percent.

Finally, the estimation procedure also requires 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.[26] 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

[24] These different steps are described in B.

[25] Note that these firms are exporters of shoes, and therefore might not be shoe manufacturers. However, since these observations are part of the consideration sets faced by foreign consumers, they are relevant to estimate the substitution patterns that characterize the demand system and are included in the estimation.

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

TABLE 3: Summary statistics for French firms

	Mean	*p5*	*p25*	*p50*	*p75*	*p95*
By firm:						
# observations	42.9	2	3	10	33	182
# destinations	5.9	1	2	3	7	20
# products	2.7	1	1	2	4	7
Price	75.8	8.8	20.8	39.9	82.6	263.9
Market share (%)	0.005	$2.6e^{-6}$	0.00004	.0003	.002	.02

Notes: FOB Prices per kilogram in Euros. Sample of 2415 firms.

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.

4.2 Demand Side Estimation

We start by presenting the algorithm to estimate the parameters of the model. Then, we describe the set of instruments used to account for price endogeneity and identify the random-coefficients parameters. Finally, we discuss potential threats to our identification.

Demand estimation algorithm In this paragraph, we describe the estimation of the parameters of our demand system: β, α, Π and Σ. Let $\theta \equiv \{\alpha, \Pi, \Sigma\}$ be the subset of parameters governing the distribution of random coefficients, as described in equation (3). As we explain below, conditional on knowing θ, β can be simply estimated by OLS. By contrast, θ is estimated using a non-linear Generalized Method of Moments (GMM) estimator. GMM algorithms rely on orthogonality conditions between a structural error term $\xi(\theta)$, function of the model parameters, and a set of instruments $Z = [z_1, ..., z_L]$ such that

$$E\left[z_l \, \xi(\theta_0)\right] = 0, \qquad \text{for} \quad l = 1, .., L \tag{13}$$

where θ_0 is the true value of the parameter.

We now describe the strategy to recover the structural error ξ_{jdt}, as a function of θ and the data. In our empirical setting, an observation is a combination of a variety j, defined by a 6-digit product category and an exporter (either a firm f or a country c), a destination market d and a year t. From equation (6), the market share of a variety j in destination d at date t is

$$s_{jdt}(\delta, x, \ln p; \theta) = \int \frac{\exp\left(\delta_{jdt} + \mu(y, \nu; x_{jdt}, \ln p_{jdt}, \theta)\right)}{1 + \sum_{j' \in \Omega_{dt}} \exp\left(\delta_{j'dt} + \mu(y, \nu; x_{j'dt}, \ln p_{j'dt}, \theta)\right)} \omega^{(1)}_{jdt}(y, \nu)\, dy\, d\nu \tag{14}$$

such that the predicted market shares depend on non-linear parameters θ, as well as on δ, x and $\ln p$, respectively the vectors of the utility term common to all consumers, observable characteristics and log-prices. This formulation provides a mapping between the vector of common utility δ and the vector of predicted market shares $s(\delta, x, \ln p; \theta)$. Therefore, conditional on the set of parameters θ and the observables $(x, \ln p)$, 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. 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 iterate using

$$\delta^{(h+1)} = \delta^{(h)} + \log S - \log s(\delta^{(h)}, x, \ln p; \theta). \tag{15}$$

until the minimum of the vector of squared difference between $\delta^{(h+1)}$ and $\delta^{(h)}$ is less than 10^{-12}.[27]

We denote the resulting vector of common utility terms $\delta(S, x, \ln p; \theta)$ and regress this vector on product characteristics x and firm dummies γ, to estimate the remaining parameter β that appears in the utility function:

$$\delta_{jdt}(S, x, \ln p; \theta) = x_j \beta + \gamma_f + \xi_{jdt}, \tag{16}$$

with f the producer of variety j. Denoting $\hat{\beta}$ and $\hat{\gamma}_f$ the estimates of equation (16), we obtain the structural errors as the residuals of this equation:

$$\hat{\xi}_{jdt}(\theta) = \delta_{jdt}(S, x, \ln p; \theta) - x_j \hat{\beta} - \hat{\gamma}_f \tag{17}$$

These structural errors $\hat{\xi}(\theta)$ allow us to compute the orthogonality conditions that identify parameter θ. This last step highlights the advantage of using GMM conditions based on the structural error rather than on the market shares predicted by the model: the only parameters that enter our GMM problem are the ones related to the distribution of the random coefficient. The other parameters (i.e. those entering the mean utility level: β and γ_f) can be directly obtained by linear regression, hence reducing the dimensionality of the search algorithm.[28]

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 $\hat{\xi}(\theta)$. Formally, we have

$$\hat{\theta} = \text{argmin}_{\theta} \quad \hat{\xi}(\theta)' Z \Phi Z' \hat{\xi}(\theta) \tag{18}$$

where Φ is the weighting matrix $\Phi = (Z'Z)^{-1}$. Moreover, we obtain standard errors for our

[27] 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. Moreover, we use 500 draws from Halton sequences to numerically approximate the integrals in the computation of $s(\delta^{(h)}, x, \ln p; \theta)$.

[28] 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 γ_f.

estimator using the GMM standard errors from Newey and McFadden (1994):

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

where G is the gradient of the objective function and $\hat{\Lambda}$ is the estimator of the covariance matrix of the vector of moments, taking into account the panel structure of the data. Specifically, we have

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

where C is the total number of producers (firm or country) and i denotes an observation. 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 $\hat{\lambda}_{jdt} \equiv \hat{\xi}_{jdt} + \hat{\gamma}_f$ for each variety j in destination d. Second, knowing the quality of each variety and the effect of income and shocks on consumers' preferences, we can now compute the distribution of choice probability $P_j(y, \nu)$ across consumers, for each variety in each destination. It follows that we can derive the optimal markup charged by a firm in a destination market, which is based on the weighted average price-elasticity of each firm. Specifically, we use equation (9) to compute the variety-specific markup that accounts for the presence of multi-product firms. Finally, markups allow us to recover the marginal costs of production: since prices are observed in the data, constant marginal costs can be obtained by dividing observed prices by the estimated markups. Therefore, it is important to note that the supply-side of the model is not used to estimate the demand system. Instead, we recover the marginal costs from the demand estimation, and will separately estimate the parameters entering the marginal cost function (7).

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 markup 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 instruments to identify the price elasticities in our demand system.[29] Specifically, we use exchange rates data from the IMF and tariffs data from the Market

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

Access Map (MAcMap) dataset that provides bilateral measures of applied tariff duties.[30]

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 an instrumental variable that varies at the firm level. To overcome this issue, we construct a firm-specific cost shifter 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 each French firm on their imports. Because 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 French firms.[31] Formally, this instrument is defined as

$$\overline{RER}_{ft} = \sum_{o \in \mathcal{S}_f} \omega_{fo} \log\left(\frac{CPI_{ot-1}}{CPI_{ft-1}} e_{oFt-1}\right)$$

where $\mathcal{S}_f$ is the set of source countries of firm f, ω_{fo} is the share of origin country o in firm f's imports, CPI_{ct-1} is the consumer price index of country c at time $t-1$ and e_{oFt-1} the exchange rate from origin o to France at time $t-1$. Importantly, the import share ω does not vary across time such that all time-variations in this instrument come 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.

In addition to these three cost shifters, we also derive instruments that will identify the distribution of the random-coefficients in our demand system. Specifically, we follow Gandhi and Houde (2017) to construct "Differentiation IVs": for each observation jdt and for each product characteristic, we count the number of French and foreign competitors identical to j in market d and year t. Similarly, for each observation jdt, we count the number of French and foreign competitors whose price differs from j's price by less than one standard deviation. In order to maintain exogeneity, we construct this measure using prices predicted from the sets of exogenous characteristics and instruments. In total, this procedure delivers ten instrumental variables: two for each product characteristic, distinguishing between the number of French competitors and foreign competitors. These ten instruments are added to the three excluded instruments presented in the previous paragraphs.

Identification conditions and adjustment for hidden varieties All three sets of instruments - product characteristics, cost shifters and differentiation IVs - are arguably exogenous to firm's demand shifters. In particular, it is very unlikely that the product quality of an individual shoe producer affects exchange rates or tariffs. However, our dataset is composed of individual French producers and of aggregate country×product-level data. The demand shifters from these aggregate trade flows depend not only on individual demand shifters, but also on the number of firms exporting from this country to a specific destination market. Formally, the structural

[30] Appendix B provides details on the dataset.

[31] See Piveteau and Smagghue (2019) for further discussion on this firm-level instrument.

error term ξ_{Jdt} for a country-product pair J in destination d at time t can be written

$$\xi_{Jdt} \equiv \log n_{Jdt} + \tilde{\xi}_{Jdt} \tag{19}$$

where n_{Jdt} is the number of firms from country-product J exporting to d in t and $\tilde{\xi}_{Jdt}$ is the average product quality of these firms. This number of hidden varieties,[32] unlike the firm-level demand shifter, is likely to be correlated with our instruments: as exchange rates or tariffs move, varieties enter or exit foreign markets, which violates our exogeneity conditions.

To address this issue, we implement a control function approach. The objective of this control function is to capture the change in the number of varieties in response to movements of our instruments, exchange rates or tariffs. By estimating the relationship between the instruments and these hidden varieties, we can control for this correlation in the structural errors of the model. As a result, the residual error term is orthogonal to the instruments, restoring the exogeneity conditions. To implement this method, we use the micro data from French exporters to estimate how the number of French varieties respond to changes in our sets of instruments, and construct a prediction for $\log n_{Jdt}$ that we use as a control in our model. Since our model contains producer fixed effects, we are only interested in the change in hidden varieties across markets and time, not the levels. Practically, we compute the number of French exporters in each product-destination-year, $\log n_{Fpdt}$ and regress this term on our set of instruments Z, as well as destination and year fixed effects.[33] This allow us to construct a prediction term $\widehat{\log n}(Z_{Jdt})$ that we include as control in our estimation. This term, only included for aggregated trade flows, allows us to control for the endogenous number of hidden varieties in the error term ξ_{Jdt}. The remaining term in the residual, the average quality of foreign exporters, is arguably exogenous to the sets of instruments and therefore does not pose a threat to the identification. In other words, the use of aggregate trade data to estimate the elasticity of trade confounds the extensive margin response and the intensive margin response. Using French data to measure the extensive margin response, we can control for this margin so that our structural parameters correctly measure the firm-level price-elasticity of demand.

In addition to posing a threat to the identification, the existence of hidden varieties might also affect the measurement of foreign competition. By using aggregate trade data, we ignore the dispersion in firm's quality and prices that exists at the microeconomic level. This heterogeneity might have a consequence on our estimation, by measuring with error the patterns of substitutions across varieties, and could also affect our counterfactual experiment that studies the effect of Chinese competition on French firms: using aggregate data in our experiment imply a different treatment than using the true underlying distribution of prices and market shares.

In the absence of a dataset that combine disaggregated trade data from all countries, we assess the implications of this aggregation bias by creating a sample that exhibits dispersion in prices within a country. Specifically, we disaggregate country-level trade flows into five distinct observations, to which we assign different prices drawn from a normal distribution. We parametrize the standard deviation of this price distribution from the observed price dispersion among French firms, and ensure that these new observations are consistent with the observed

[32] See Feenstra (1994) and Khandelwal (2010) for discussions on this issue.

[33] We report results of this regression in table 9 of appendix E

aggregate data. Using this new simulated dataset, we rerun our estimation procedure and our counterfactual experiments. Details and results of this procedure are displayed in appendix D. We find that this dispersion has little impact on both our estimates and the results of our counterfactual experiments. Even though this procedure is an imperfect test, it is reassuring that the measurement issues created by the use of aggregate data do not have a strong impact on our results.

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 quantify the extent of this response, it is necessary to measure the cost of producing higher quality. Fortunately, the model provides guidance on how to discipline this source of adjustment.

First, the first order condition on quality highlights how the convexity in the cost function, through the parameter h, shapes this response. Rewriting this first order condition from equation (12), we have:

$$\lambda^*_{jdt} = \frac{1}{2h}\left(\tilde{\alpha}^{-1}_{jdt} - \eta_{jdt}\right)$$

with α_{jdt} defined in equation (12). From this equation, we know that optimal quality λ^*_{jdt} is a linear function of inverse demand elasticity $\tilde{\alpha}^{-1}$. Moreover, the slope of this relationship being equal to $\frac{1}{2h}$, parameter h can be estimated from the regression of λ on $\tilde{\alpha}^{-1}$.

Moreover, we can derive a second linear regression that can identify the parameter h. Combining the marginal cost function (equation (7)) and the first order condition on quality leads to the following formulation of the marginal costs:

$$\ln c_{jdt} = x_{jt}\rho + \frac{1}{4h}\left(\tilde{\alpha}^{-1}_{jdt}\right)^2 - \frac{1}{4h}\eta^2_{jdt} + \varphi_{jdt}. \tag{20}$$

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 is unlikely to consistently identify h because of simultaneity issues: changes in the average price-elasticity of a firm, $\tilde{\alpha}$, can be due to changes in its competitive environment but also to changes in its own cost parameters. In particular, a reduction in the cost of producing quality η_{jdt} would make a firm move up the quality ladder and thus 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 foreign competition that are exogenous to the firm. As such, this instrument is orthogonal to 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 the characteristics of its competitors:

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

where δ_{jd0} denotes the initial δ of producer j in destination d. This instrument captures changes in the incentives of making quality triggered by changes in the competitive environment. Firms differ in their initial characteristics, but the time variation of this instrument is only due to changes in the characteristics of competitors , $\sum_{j'\notin F}\exp(\delta_{j'dt}+\mu_{j'dt}(y,\nu))$, 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 and marginal cost responses.

We use this instrument to consistently estimate the relationship between quality and average price elasticity, equation (12), and between marginal cost and the square of the average price elasticity, equation (20). From these regressions, we can obtain estimates of h that will allow us to perform our counterfactual experiment.

5 Estimation Results

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

5.1 Demand Estimation Results

Before describing the results of our estimation with random coefficients, we start by estimating a standard logit model: we regress the normalized logarithm of the market share $\log s_{fdpt} - \log s_{0pdt}$, on product characteristics, log of price, an interaction between the log of the price and the average log income in the destination, and producer dummies. This specification corresponds to a special case of our demand system in which consumers are homogeneous within destinations. The advantage of this specification is to deliver a linear equation, estimable with 2SLS, which allows us to assess the effectiveness of our instrumental strategy. In columns (1) and (2) of table 4, we respectively report the results of an OLS regression and a 2SLS estimation that uses the three cost shifters described in the previous section as instruments. While the OLS regression in column (1) displays unrealistic positive price elasticity estimates, results from column (2) validates our instrumental variables strategy. First, the first stage F statistics is equal to 34, which shows that our set of instruments is strongly correlated with prices. Second, we find that the use of instruments does correct the price estimates in the right direction. Using our instruments, we obtain realistic price elasticities, equal to -2.90 in the average destination, and positively correlated with the average income of consumers in the foreign destination.[34] Therefore, destinations with richer consumers display a demand for foreign varieties that is less price-elastic.

We now turn to specifications (3) and (4) that include random coefficients on the price elasticity and the preference for French goods. We allow each of these parameters to vary with the log income of the consumer, through parameter Π, and with an unobserved source of variation with parameter Σ.[35] In all specifications, we cannot identify the average valuation for French goods due to the inclusion of producer fixed effects. While columns (3) and (4) display the same structure of random coefficients, we only implement our control function approach in column (4). In this specification, we control for hidden varieties by including a control function estimated using micro-level French data.

Both specifications emphasize the importance of allowing for heterogeneity in preferences. As expected, we find a larger price-elasticity with specification (3): since this specification does not include our control function, the price-elasticity is biased by confounding the extensive margin effect with the intensive margin effect. Regarding the role of random coefficients, we can see in all specifications that richer consumers are significantly less price-elastic (coefficient Π_{α}), but do not tend to have a specific 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.

These specifications also document some dispersion in preferences driven by other types of heterogeneity. First, we find that Σ_{French} is significantly different from zero which means that consumers differ in their preferences for French goods, even after controlling for income. This implies that a French variety is more substitutable to another French variety relative to a foreign one. Similarly, Σ_{α} being significant implies that the heterogeneity in price-elasticity across consumers is also driven by factors different than income. This heterogeneity will make patterns of substitution between varieties even more sensitive to their proximity in the price space.

Finally, specification (5) is our most preferred specification as it includes random coefficients on all characteristics. This results in a total of 12 random coefficients, the valuation of each of the six observables characteristics being able to vary with income and another source of unobserved heterogeneity. Once again, we find that consumers' income matter in the valuation of product characteristics and in particular of prices: while a consumer with an average income has a price-elasticity of -2.44 ($-\exp(0.89)$), a consumer with a 10 percent higher income will have a price-elasticity of -2.30 ($-\exp(0.89 - 0.1 \times 0.58)$). Finally, we also find strong substitution patterns between French firms: because some consumers are particularly attached to French products, these French firms display stronger substitution between them.

Having described these parameter estimates, we now describe several outcomes of the model which further illustrate the implications of heterogeneous preferences. Specification (5) is the most complete one as it includes random coefficients on all characteristics. Therefore, we use it as a baseline in the rest of the paper, both for our post-estimation analysis and our counterfactual

[34] The income in the destination is normalized such that it equals zero for the average country.

[35] We assume that consumer-specific shocks on preferences, that identify Σ, are normally distributed and independent across product characteristics.

Table 4: Estimation results

	OLS	2SLS	Random coefficients								
	(1)	(2)	(3)			(4)			(5)		
			Mean	Π	Σ	Mean	Π	Σ	Mean	Π	Σ
log price	0.20***	−1.90***									
	(0.056)	(0.24)									
log price $\times$ inc_d	0.41***	0.74***									
	(0.054)	(0.22)									
α			1.40***	−0.34***	−0.30*	1.07***	−0.45***	−0.37*	0.89***	−0.58***	0.40
			(0.08)	(0.08)	(0.17)	(0.11)	(0.11)	(0.19)	(0.18)	(0.19)	(0.36)
French			.	0.08	5.38***	.	0.14	5.03***	.	−0.25	4.71***
				(0.27)	(0.25)		(0.27)	(0.24)		(0.35)	(0.42)
Leather sole	−1.04***	−1.13***	−1.35***	.	.	−0.99***	.	.	−0.89	−0.43**	−0.50
	(0.11)	(0.14)	(0.17)			(0.15)			(1.80)	(0.18)	(4.72)
Leather top	1.16***	0.97***	0.84***	.	.	0.45***	.	.	0.26*	0.83***	0.069
	(0.11)	(0.12)	(0.16)			(0.14)			(0.14)	(0.22)	(1.30)
Fabric top	−0.045	−0.018	−0.02	.	.	−0.23**	.	.	−0.93	1.09***	-0.76
	(0.079)	(0.098)	(0.12)			(0.11)			(2.89)	(0.26)	(5.85)
Boot	−0.57***	−0.58***	−0.53***	.	.	−0.26***	.	.	−0.33**	0.091	-0.54
	(0.059)	(0.064)	(0.08)			(0.062)			(0.16)	(0.11)	(0.72)
Control function	No	No	No			Yes			Yes		
R^2	0.55										
First stage F-stat		34.3									

Notes: Number of observations: 193 927. Standard errors between parentheses clustered at the producer level. All specifications include producer (firm or country) fixed effects. Instruments for specification (2) are the three cost shifters and their interaction with the destination log average income. Specifications (3) and (4) use the following instruments: product characteristics, the three cost shifters, the logarithm of the number of predicted prices within one standard deviation, the logarithm of the number of French predicted prices within one standard deviation, and an interaction between the cost shifters, a French dummy and the average income on the destination (total of 13 instruments). Specifications (5) uses the same set of instruments, plus the number of foreign and French competitors with the same product characteristics, and an interaction between product characteristics and income in the destination (total of 25 instruments). Significance levels: * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

experiments.

5.2 Demand Estimation Outcomes

To highlight the role of consumer heterogeneity in creating dispersion between firms regarding their market power or their exposure to competition, we now describe the distribution of markups, price elasticities and cross-elasticities with Chinese exports.

The first interesting feature of the model is the existence of heterogeneous markups across firms. Because firms differ in characteristics, they serve consumers with different price elasticities. As a consequence, they charge a markup that differs depending on their average consumer. Figure 3 displays the resulting distribution of multiplicative markups across French firms. The unit of observation is a specific variety in a foreign market at a given time. These markups are directly computed from equation (9), using parameter estimates from specification (5) in table 4 to parametrize the distribution of consumer preferences. The average markup among French varieties is around 65 percent, which is at the higher end of estimates found in the literature. This could be due to the fact that French shoes tend to be relatively high-quality shoes on average, targeting wealthy consumers. Interestingly, we see a large variation in these markups: some products only have a 10 percent markup, while others are above 100 percent.

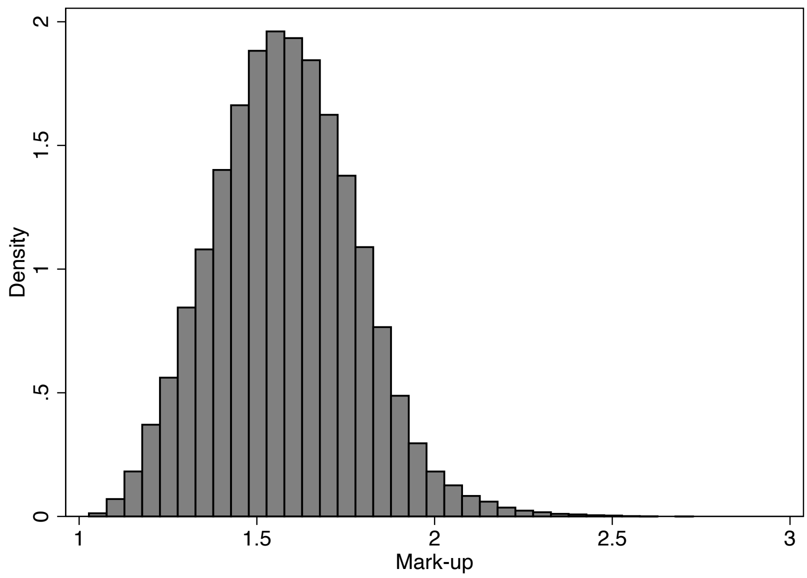

FIGURE 3: Distribution of markups of French firms

This dispersion in markups across firms can have two origins. First, firms with larger market shares in a destination country will exert oligopoly power by raising their prices. Alternatively, firms with higher quality will serve consumers who tend to have a lower price elasticity. As a consequence, it is optimal for these firms to charge a higher markup over their marginal costs. In order to identify which of these factors drive the observed dispersion in markups, we report in figure 4 the relationship between markups and the logarithm of the market share (left panel), and between markups and quality (right panel).[36] This figure shows that most of the variation in profit margin comes from the position of the firm in the quality ladder: low-quality firms

[36]Quality measures are negative since they are defined relative to the demand shifter of the domestic variety in the foreign country.

tend to have much smaller markups. 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 markup for their product. On the contrary, firms with higher quality products face consumers with lower dis-utility from high prices and can therefore set higher markups. By contrast, we do not find a significant effect of market shares on markups: the market shares of French firms in destination markets are too small to lead them to any oligopolistic pricing behavior.

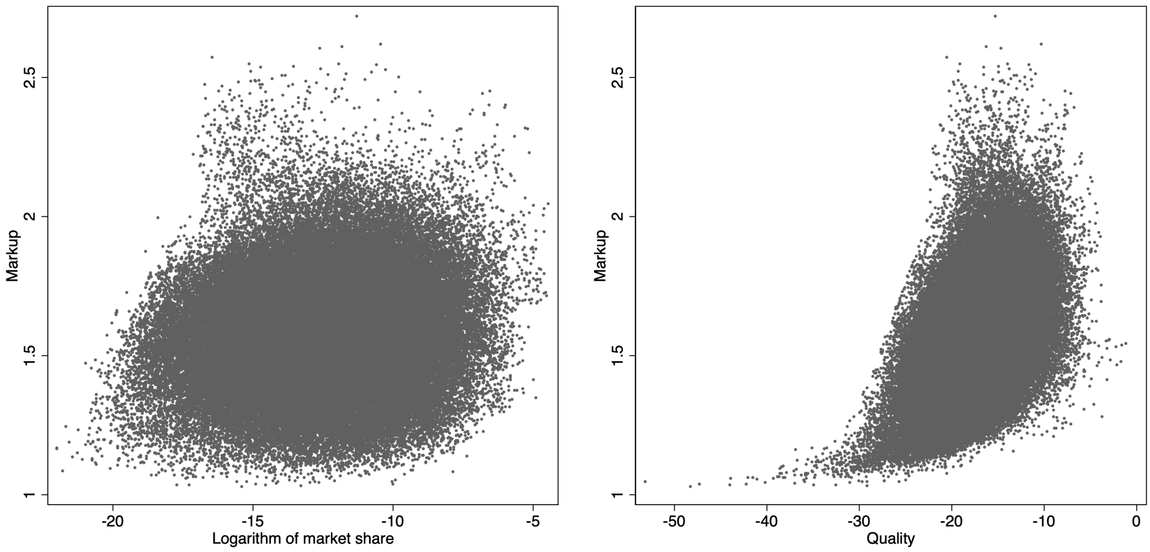

FIGURE 4: Correlation of markup with market share and quality

Finally, the introduction of random coefficients to capture consumer heterogeneity also generates dispersion in the price-elasticities faced by French firms. This is true for their own-price elasticity, but also for the cross-price elasticities with respect to foreign competitors. In other words, these random coefficients give rise to different levels of exposure to foreign competition. To quantify this dispersion, figure 5 plots the distribution of own price-elasticity among French firms (left panel), and their cross-elasticity with Chinese exports (right panel). These elasticities are computed as follows:

$$\frac{\partial \log s_{jdt}}{\partial \log p_{jdt}} = \int (1 - \mathbb{P}_j(y,\nu)) \, \exp(\alpha(y,\nu)) \, \omega_j^{(2)}(y,\nu) \, dy d\nu,$$
$$\frac{\partial \log s_{jdt}}{\partial \log p_{j'dt}} = \int \exp(\alpha(y,\nu)) \, \mathbb{P}_{j'dt}(y,\nu) \, \omega_{jdt}^{(2)}(y,\nu) \, dy \, d\nu,$$

and for any French variety jdt, we obtain the cross price-elasticity to China by taking the sum of cross price-elasticities across all varieties j' exported by China to destination d at time t.

From the left panel of figure 5, we can see a large dispersion in price-elasticity, ranging from -2 to -8. This dispersion similarly reflects the fact that firms face very different average consumers, affecting their optimal response in terms of prices. The right panel of figure 5 shows that serving different consumers also implies that firms are unequally affected by low-cost competition. A large share of French firms are barely affected by Chinese prices, while some firms have a cross-price elasticity larger than one, emphasizing their strong similarity to Chinese products: firms with low prices are specifically selling to consumers who, given their preference for low-price products, are likely to turn to Chinese producers when the supply of Chinese products increases.

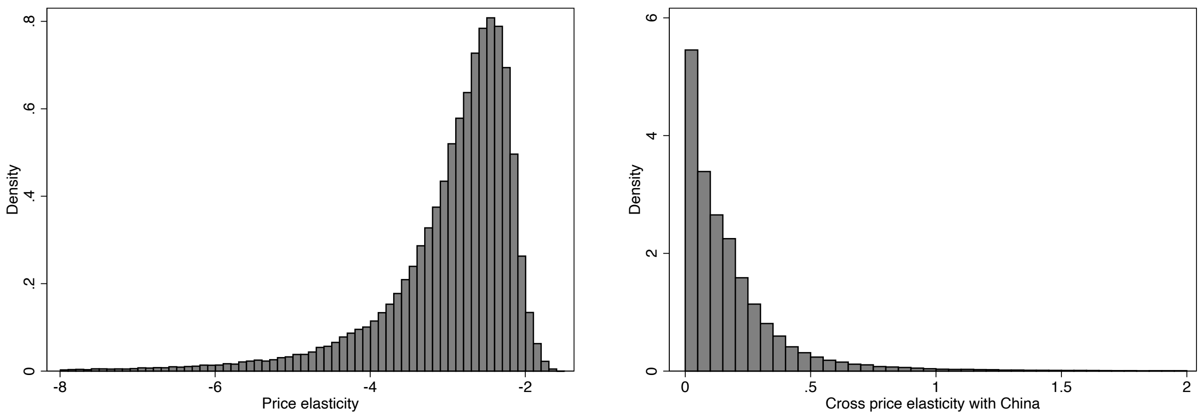

FIGURE 5: Distribution of own and cross-price elasticities (French firms).

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 sample period, as they intend to escape Chinese competition. This prediction is confirmed by figure 6 that reports the relative average quality of French exporters over time, depending on their position in the price distribution in 1997. To create this figure, we divide French exporters into price quartiles in 1997, and compute the average quality of each quartile-year group across destination markets. We then normalize these average quality levels, so that the quality of the top quartile stays equal to zero over the period. We can see that firms with low prices and low quality in 1997, 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.[37]

This convergence of quality across French firms is concurrent with the documented increase in low-cost competition in the footwear industry. However, even though this result is suggestive of some relationship between competition and quality adjustment, many other factors could explain this correlation: changes in technology, input prices or preferences could all be reasons that lead French firms to upgrade the quality of their products during this period. In order to isolate the effect of the China shock and the quality response by French firms, we use our model to implement a counterfactual experiment in section 6. Before discussing these counterfactuals, we now present our estimates of the impact of quality upgrading on firm costs, that will discipline

[37]Note that the quality estimates used in figure 6 are obtained from estimating the demand side of the model only. Therefore, we do not assume that firms behave optimally and upgraded their quality in response to Chinese competition.

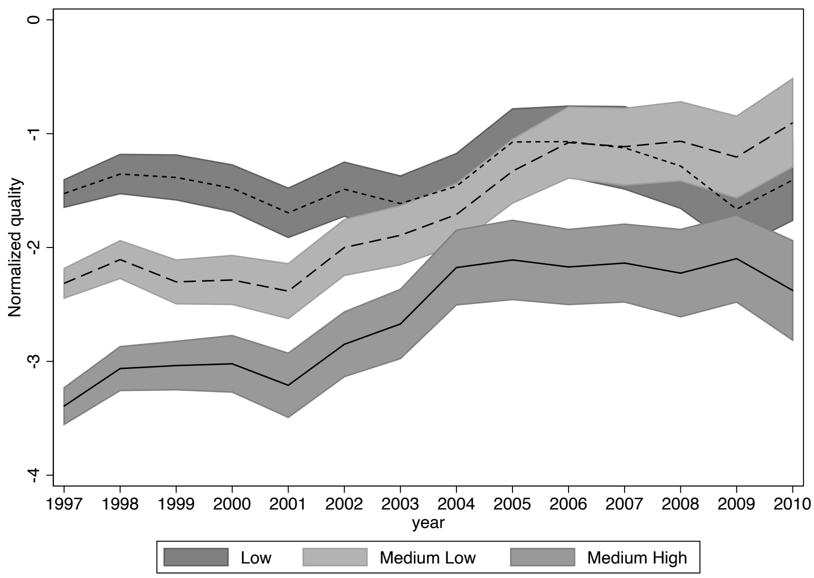

FIGURE 6: Low Price Varieties Upgrade their Quality over the Period

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.

the quality response in our counterfactuals.

5.3 Estimation of the cost of quality upgrading

The model described in section 3 allows firms to choose the optimal quality of their product. In order to ensure that firms choose a finite level of quality, we imposed a convexity in the cost of quality: as firms upgrade the quality of their product, the marginal cost of production increases at a quadratic rate.[38] As a consequence, the parameter h that governs the curvature of the relationship between marginal costs and quality also disciplines the extent to which firms will adjust their quality in response to a competition change. In section 4, we provide two equations to identify this parameter h. First, the first order condition on quality, equation (12), identifies this parameter through the link between the optimal quality of a variety and its inverse average price-elasticity $\tilde{\alpha}^{-1}$. Second, the change in the marginal costs of production in response to changes in the square of $\tilde{\alpha}^{-1}$ also allows us to identify parameter h (see equation (20)).

We present the estimation results using both specifications in table 5. Because these reduced-form specifications deliver different structural parameters, we divide the square of $\tilde{\alpha}^{-1}$ by two so that both specifications estimate the same structural parameter $\frac{1}{2h}$. The first three columns show the regression of the quality measure on $\tilde{\alpha}^{-1}$, while columns (4)-(6) the regressions of the marginal cost on $\frac{(\tilde{\alpha}^{-1})^2}{2}$. Finally, since they estimate the same parameter, we combine both specifications in the last two columns, by stacking observations from both regressions, in order to obtain a single estimate of h. In both specifications, we first report the OLS regression (columns

[38]To confirm that the relationship is indeed quadratic, figure 13 in appendix E compares the fit of a quadratic and non-parametric regression between marginal costs and quality, and shows that the quadratic approximation performs well.

1 and 4), the reduced form relationship between our dependent variable and the instrument created to address the endogeneity issue described in section 4 (columns 2 and 5), and finally the IV specification to obtain an estimate of $\frac{1}{2h}$ (columns 3 and 6). Finally, we show the OLS and IV results of our stacked specification in columns (7) and (8). Because our identification relies on the time-variation of our instrument, we use first difference to estimate how an exogenous change in competition leads to a change in the average price-elasticity of a firm's consumers, which triggers a change in optimal quality. Moreover, all specifications include destination-year fixed effects such that the identification takes place between varieties exporting to the same destination market.

TABLE 5: Estimation results: supply side

	quality λ_{jdt}			$\log mc_{jdt}$			*Stacked*	
	OLS	RF	IV	OLS	RF	IV	OLS	IV
$\tilde{\alpha}^{-1}$	12.3***		**2.98**					
	(0.20)		(2.30)					
$\frac{(\tilde{\alpha}^{-1})^2}{2}$				6.64***		**2.10****		
				(0.080)		(0.65)		
$\tilde{\alpha}^{-1}$ or $\frac{(\tilde{\alpha}^{-1})^2}{2}$							10.7***	**2.78**
							(0.19)	(1.84)
$instr_{jdt}$		2.21						
		(1.86)						
$instr^2_{jdt}$					0.66**			
					(0.28)			
$\hat{h}$			**0.168**			**0.238**		**0.180**
N	60 919	60 867	60 867	60 919	60 867	60 867	121 838	121 734
R^2	0.41	0.065	0.16	0.89	0.018	0.47	0.41	0.17
F first-stage			84.6			53.9		48.9

Notes: Firm-level clustered standard errors between parentheses. All regressions are estimated in first differences and include destination-year fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5 validates our instrumental strategy: the OLS estimates are large in all three specifications because endogenous quality choice generates spurious correlation between quality or marginal costs and the inverse price elasticity or its square. In columns RF, we show that our instruments have the expected effect on our dependent variables. A change in competition, that makes the average consumer faced by French firms more inelastic, leads to an increase in the quality of French firms, as well as in their marginal costs. Finally, we use our instrument in a 2SLS framework to obtain our structural estimates. As expected, we find a much smaller coefficient when using our instrument, which eliminates the spurious correlation between quality and the inverse elasticity. Since the IV specifications identify the parameter $\frac{1}{2h}$, estimates of 2.98 and 2.10 lead to a value for $\hat{h}$ of respectively 0.168 and 0.238. A possible explanation for this difference could be that quality upgrading entails other costs beside marginal costs. In that case, we would identify a smaller impact of quality on marginal costs, because marginal costs only capture one aspect of the additional cost of quality.[39] Moreover, it is important to

[39]While it would be interesting to study the consequences of quality upgrading on the different costs of the

recognize that these parameters come with large confidence intervals. In order to settle on one specific value for our counterfactual experiment, we stack both specifications into a single linear regression, which allows us to estimate a single value for parameter h, taking advantage of both structural relationships. This specification leads to an estimate of 2.78 for $\frac{1}{2h}$, which implies a value of 0.18 for h. Therefore, we use a baseline value of 0.18 for the parameter h in our counterfactual exercise, and will document that our results are not very sensitive to this value in the appendix.[40]

Incidentally, 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 form predictions as to the performance of shoe producers in an alternative environment to the one actually observed in the data. In particular, we use the model to isolate the impact of the rise of China in the footwear market, and study its implications on French exporters. As we study the impact of Chinese competition, 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.[41] We start by describing the counterfactual experiment and presenting the results in a simple case where French firms cannot respond to the shock, be it by adjusting their markup or their quality. Then, we move gradually to a scenario where firms are allowed to fully respond and we document the quantitative importance of the different margins of adjustment.

6.1 Experiment with Fixed Quality and markup

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 fix the fundamentals of Chinese producers to their post-2007 levels, while maintaining the characteristics of other countries and firms to their values in 1997. Specifically, for each Chinese variety in each destination market, we compute the average price and demand shifter from 2008 to 2010. We then solve the model using these new characteristics for Chinese exporters and 1997's characteristics for French firms and other countries. Solving the model with this set of fundamentals, and comparing it to the actual scenario in 1997, we can identify the effect of the increasing Chinese competition on French firms.

To get a sense of the magnitude of our experiment, we report in figure 7 the evolution of Chinese fundamentals in terms of average log normalized price $\ln p_{jdt} - \ln p_{0dt}$ and average

firm, this type of analysis is beyond the scope of this paper.

[40]Figures 15 and 16 in appendix E show that our counterfactual results are qualitatively similar when using $h = 0.16$ or $h = 0.24$.

[41]Note that the growth of Chinese export capabilities has also improved the sourcing opportunities for French firms. However, in this experiment, we restrict our attention to the competition effects of the China shock.

demand shifter λ_{jdt}. It appears from this figure that most of the rise of Chinese market shares over the period is driven by an increase in the demand shifter rather than a drop in prices. It means that most of the growth of Chinese exporters comes from an increase in the average quality of their exports or in the number of varieties exported.

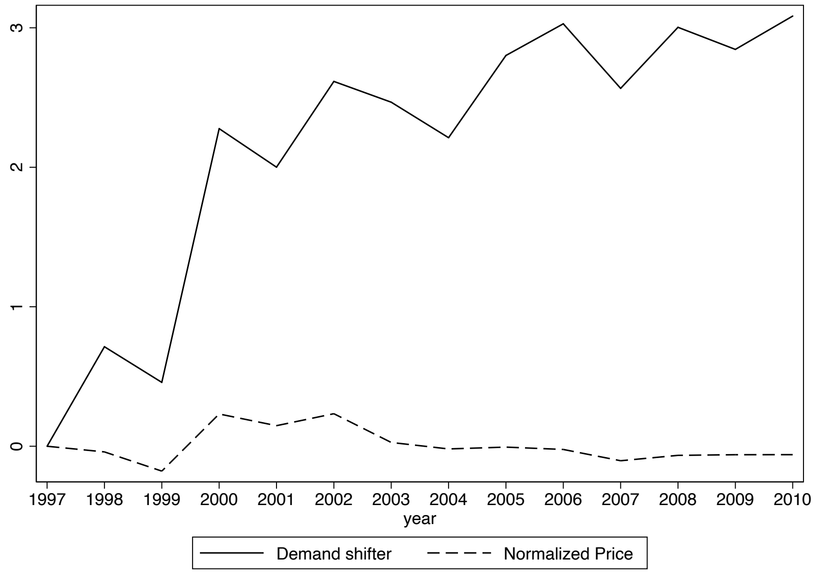

FIGURE 7: Average Chinese Price and Demand Shifter over Time

Notes: The figure reports the evolution of Chinese exports in terms of demand shifter and log price (normalized by the price of the outside good).

In the first version of our counterfactual experiment, we do not allow the price and quality of French varieties to change in response to the shock. Under this assumption, it is straightforward to use equation (6) to recompute the new French market shares and profits under the counterfactual set of Chinese fundamentals, and compare them to the actual market shares in 1997.

We present the results of this counterfactual experiment in figure 8. Specifically, we compare the actual 1997 market shares relative to the scenario in which prices and quality of Chinese producers are set at their post-2007 level. 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.[42] Firms at the bottom of the price distribution see their market shares decrease by more than 20 percent. On the contrary, firms at the top of the price distribution only experience a 12 percent reduction in their market share. Therefore, even though all firms lose from Chinese competition, low-price firms lose disproportionately. In this specific scenario in which French markups do not adjust, this loss of market shares translates into an exactly proportional loss of profits.

These results highlight the importance of capturing complex substitution patterns between producers. In a CES world, all French firms would be equally affected by the rise of Chinese competition. Instead, we show that the substitution patterns are such that low-price French

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

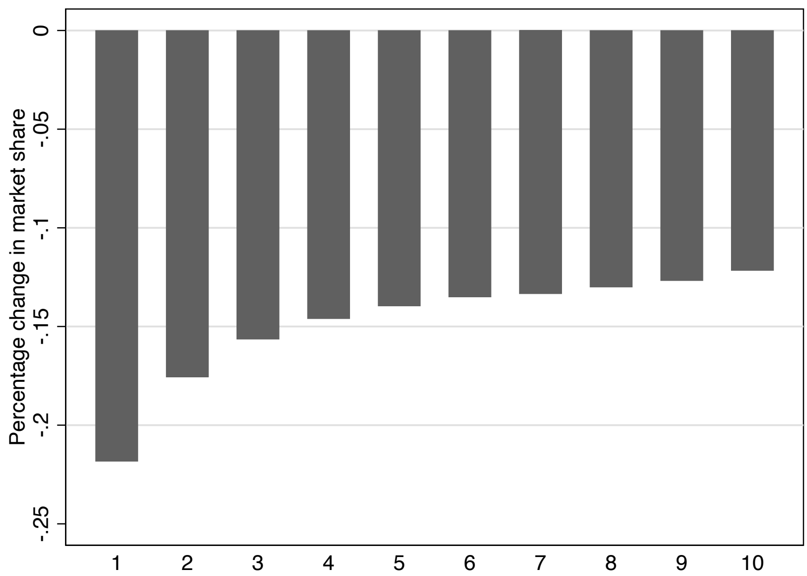

Figure 8: Effect of the China shock by price deciles (on French firms in 1997)

Notes: The figure reports the median log-change in market shares for all French firms in 1997, separately for each price decile. The change is measured between the true scenario and the counterfactual scenario in which China increases its 1997 fundamentals to its post 2007 levels.

firms are much more vulnerable to low-cost competition. As a consequence, they will lose much more market shares from Chinese competition. Moreover, it is important to note that these effects are measured without taking into account the potential effect of the China shock on firm entry and exit decisions. In the stylized facts from section 2, we find that low-cost competition causes more exit among low-price varieties than among high-price varieties. This suggests that accounting for an extensive margin would probably amplify the concentration of losses on cheap varieties. In that sense, our counterfactual results can be seen as a lower bound to the differential effect of China along the price distribution.[43]

In conclusion, these results imply that it is now more appealing to be located at a higher point in terms of quality and price: as Chinese firms increase the local competition for low-price varieties, French firms have more incentives to escape this competition by moving up the quality ladder. We study this quality and price responses in the next subsection.

6.2 Accounting for Markup and Quality Adjustment

The demand system estimated in the previous section implies that firms may want to adjust their markups and 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 markup and quality adjustments. Once again, we implement our experiment by setting the prices and quality of Chinese producers to their post-2007 levels, and look at the effects of these Chinese fundamentals on French firms in 1997. Importantly, we only allow French firms to adjust their

[43] 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. Therefore, we decide to focus on intensive margin adjustments.

markup and quality levels, leaving unchanged the characteristics of other foreign exporters.[44]

The new equilibrium quality, markups and marginal costs are computed such that the pricing equation (9), the first order condition on quality (11) and the marginal cost equation (7) are verified for all French firms. Starting from initial equilibrium values $\left\{M_{jdt}^{(0)}, c_{jdt}^{(0)}, \lambda_{jdt}^{(0)}\right\}$, we find the counterfactual equilibrium by iterating over the following set of equations:

- We update the choice probability of each consumer given the new set of fundamentals:

$$\mathbb{P}_{jdt}^{(s)}(y,\nu) = \frac{\exp\left(\delta_{jdt}^{(s)} + \mu_{jdt}^{(s)}(y,\nu)\right)}{1 + \sum_{j\in\Omega_{dt}} \exp\left(\delta_{jdt}^{(s)} + \mu_{jdt}^{(s)}(y,\nu)\right)}$$

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

- Given these new probabilities, we recompute the optimal markup and quality levels chosen by French firms:

$$M^{(s+1)} = \left(I + \Delta^{(s)}\right)^{-1} \Delta^{(s)}$$
$$\lambda_{jdt}^{(s+1)} = \lambda_{jdt}^{(0)} + \frac{1}{2h}\left(\left(\tilde{\alpha}^{(s+1)}\right)^{-1} - \left(\tilde{\alpha}^{(0)}\right)^{-1}\right)$$

  with $\tilde{\alpha}^{(s+1)} = \frac{\Delta^{(s)}(1-M^{(s+1)})}{G^{(s)}(1-M^{(s+1)})}$. $G^{(s)}$ and $\Delta^{(s)}$ are defined as in section 3 but using the updated choice probabilities $\mathbb{P}_{jdt}^{(s)}(y,\nu)$.

- Finally, we update the marginal cost of production:

$$\log c_{jdt}^{(s+1)} = \log c_{jdt}^{(0)} + \left(\tilde{\alpha}^{(0)}\right)^{-1}\left(\lambda_{jdt}^{(s+1)} - \lambda_{jdt}^{(0)}\right) + h\left(\lambda_{jdt}^{(s+1)} - \lambda_{jdt}^{(0)}\right)^2,$$

  which, combined with the new markup rule $M^{(s+1)}$, allows us to construct the new equilibrium price $p^{(s+1)}$ for each firm.

We iterate these steps until convergence to obtain the equilibrium prices, quality and marginal costs of all French firms under this new environment. Because we are solving this new equilibrium relative to the existing equilibrium, we do not need to estimate all the fundamentals of the model such as productivities φ_{jdt} or the idiosyncratic cost of quality η_{jdt}.[45] We then compare this new equilibrium to the one in which Chinese fundamentals have not changed to quantify the effect of the China shock on market shares, profit, markups and quality. Specifically, we compare equilibrium under three scenarios: one in which French firms maintained their quality and markups (similar to the previous section), one in which they can endogenously change their markups, and one in which they can change both their markups and the quality of their product.

[44] We do not allow foreign countries to adjust their markups and quality since this would require using the model to back out country-level markups to measure marginal costs. 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 markups. As a result, we decide to maintain prices and qualities of non-French varieties as estimated from the data.

[45] This result is similar to the exact hat algebra procedure introduced in Dekle, Eaton, and Kortum (2008). We show in appendix A the derivations of the equations that allow us to iterate on the optimal quality and marginal costs from the initial equilibrium, without solving for the fundamentals of the model.

Results are reported in figure 9. As one can see from the light grey elements on the figure, firms find it optimal to increase their markups: because Chinese firms have relatively low prices, French firms lose their most price-elastic customers to Chinese competitors and increase their price in response. Therefore, while the model accounts for oligopoly power and could predict a reduction in markup through a pro-competitive effect, the change in the price-elasticity of the average consumer served by French firms is the dominating force, leading to a rise in markup.[46]

This adjustment is the largest at the bottom of the price distribution: assuming fixed quality, median markup increases range from 4% in the first price decile to less than 1% in the top decile. The implications of larger markups for profits and market shares are significant and contrasted. On the one hand, the loss of market shares is amplified. On the other hand, larger markups mitigate the impact of the China shock on profits as firms extract larger margins out of each unit sold. This is particularly true among cheap varieties: endogenous markups reduce by 3 percentage points the median profit loss in the first price decile while profit loss is essentially left unchanged in the top decile.

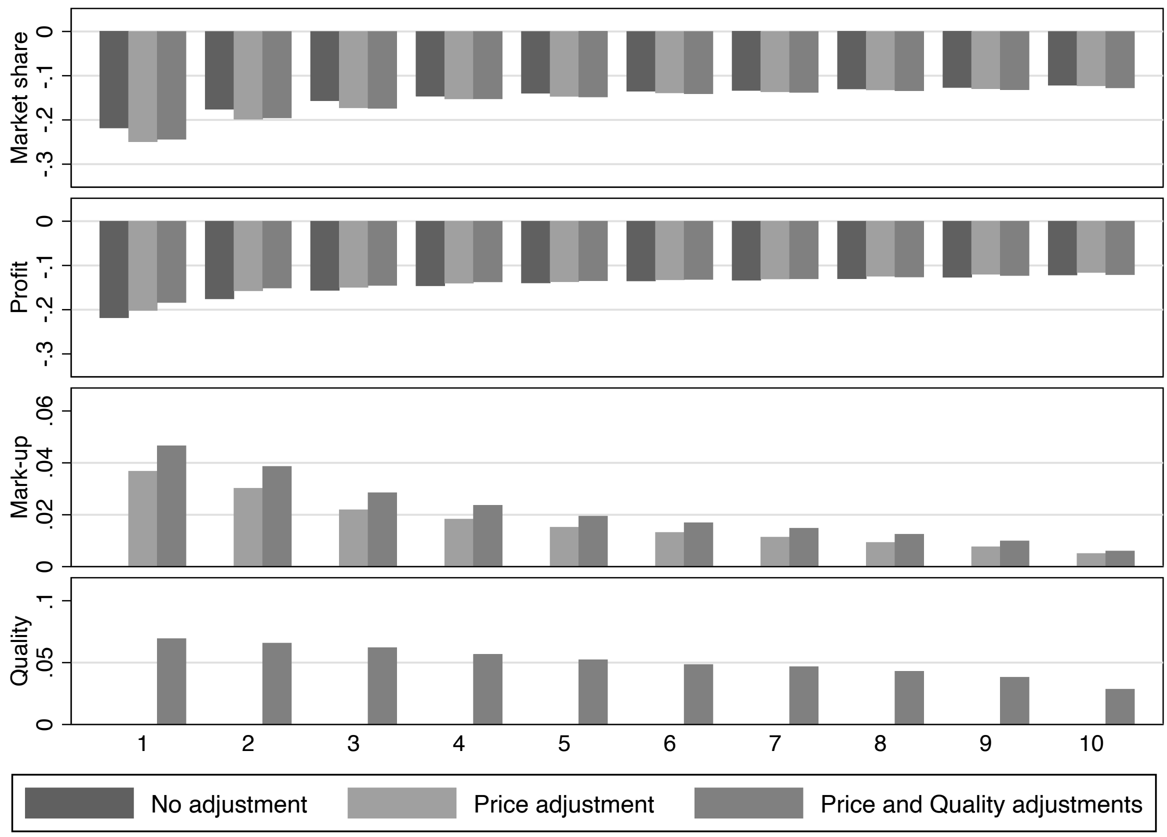

FIGURE 9: Effect of the China shock and the quality response

Notes: The figure reports the median log-change in market shares, markups, profit and quality for all French firms in 1997, separately for each price decile. The change is measured between the true scenario and the counterfactual scenario in which China increases its fundamentals to their post 2007 levels.

From figure 9, it appears that product quality also matters for the consequences of the

[46]While a large literature documents the pro-competitive effects of trade (see Edmond, Midrigan, and Xu (2015) or Bellone, Musso, Nesta, and Warzynski (2014) for instance), in our context French firms are too small in foreign markets to exert market power.

China shock. First of all, the bottom panel shows that all French firms upgrade their quality: as Chinese products gain market shares, consumers who persist in buying French products are on average richer and thus more willing to pay for quality. This is especially true for firms located at the bottom of the price distribution, where Chinese firms concentrate. This quality increase is also reflected in markups: we see that French firms tend to increase their markup even more when quality is endogenous. This is because firms face less price-elastic consumers as their production costs increase from quality upgrading.

When it comes to profits, the quality response of French firms appears to have a significant but limited effect. In fact, only firms in the lower half of the price distribution reduce 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 product quality. While this result can be explained by a large cost of producing higher quality, we show in appendix E that this conclusion is robust to using different values for h, the parameter that disciplines this quality response.[47] It indicates that this mechanism only offers limited relief for firms aiming at mitigating the adverse effects of low-cost countries competition. Interestingly, for firms at the top of the price distribution, profits losses are larger under endogenous quality. This is because quality upgrading at the bottom of the price distribution triggers a "ripple effect": while high-quality firms do not experience a strong direct impact of Chinese competition, they suffer indirectly from the quality adjustments of other French varieties which intensify the competition in the high-quality segment.

In conclusion, while quality adjustments help low-quality firms mitigate the China shock, they do so in very limited proportions such that the effects of this shock remain large and heterogeneous across firms.

6.3 Replicating the Heterogeneous Effect of the China Shock

To conclude the description of our counterfactual experiment, we assess the extent to which the increase in low-cost competition alone can replicate the unequal trend between low-price and high-price shoe producers highlighted in figure 1. To do so, we run our model holding the characteristics of French exporters at their average pre-2001 levels, but allowing 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 the fundamentals of French exporters (productivity and cost-elasticity of quality). However, we do allow French firms to adjust their quality and markup in response to these changes in competition. Figure 10 shows that a significant share of the divergence in performance between high-price and low-price French firms can be explained by the model. Overall, our results suggest that the rise of foreign competition from low-cost countries can explain more than half of the dispersion between the observed trajectories of low-price and high-price firms in foreign markets during the sample period.

[47] We verify in figures 15 and 16 that the conclusions are similar when using different parameter values for h.

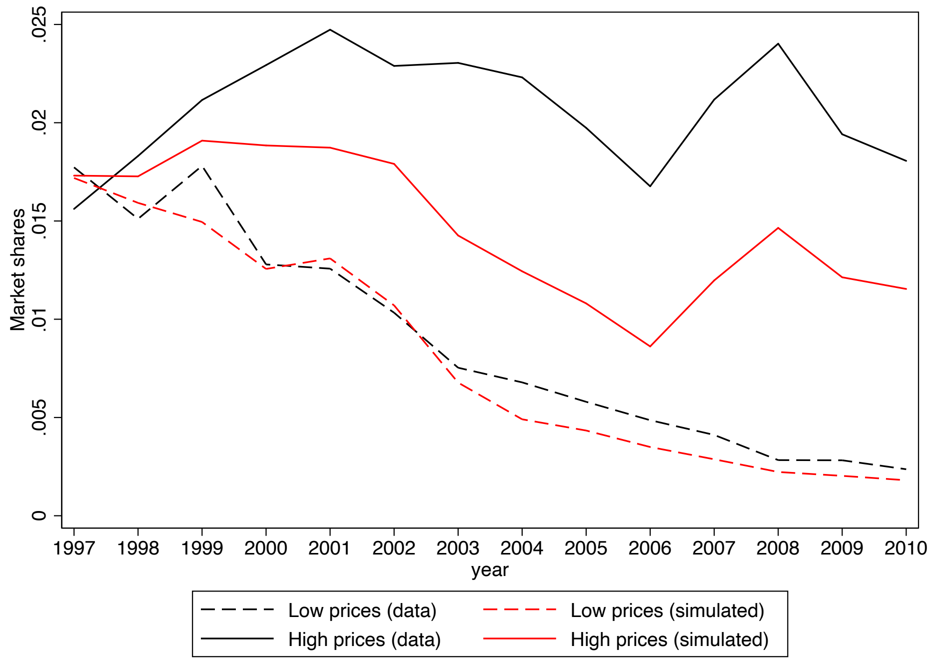

FIGURE 10: Role of the change in competition.

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

7 Conclusion

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

We estimate our model using export data from the footwear industry and find evidence of heterogeneity in consumers' preferences. To understand how these patterns shape the impact of trade across firms, we implement counterfactual experiments on the "China shock". Over the period 1997-2010, We find that in terms of market shares, Chinese competition was twice more damaging to French firms at the bottom of the price distribution than at the top. Interestingly, the quality response of French firms did little to mitigate the impact of trade with China.

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

Derivation of the optimal price The profit of the firm is

$$\Pi_f = \sum_{j \in F} r_j \left(1 - \frac{c_j}{p_j}\right).$$

Therefore, the first order conditions associated with each price p_j is

$$\begin{aligned} \frac{\partial \Pi_f}{\partial p_j} = 0\,, \quad \forall j \in F \qquad &\Leftrightarrow \quad r_j \frac{c_j}{p_j^2} + \sum_{j' \in F} \frac{\partial r_{j'}}{\partial p_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0\,, \quad \forall j \in F \\ &\Leftrightarrow \quad \frac{c_j}{p_j} + \sum_{j' \in F} \frac{p_j}{r_j}\frac{\partial r_{j'}}{\partial p_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0\,, \quad \forall j \in F \end{aligned}$$

Moreover, we have

$$\begin{aligned} \frac{\partial r_{j'}}{\partial p_j} &= \frac{\partial}{\partial p_j}\left\{\int \frac{\exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)}{1 + \sum_{j' \in \Omega} \exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)} e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu\right\} \\ &= \int -\frac{\partial \mu_j(y,\nu)}{\partial p_j} \frac{\exp\left(\delta_j + \mu_j(y,\nu)\right)\exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)}{\left[1 + \sum_{j' \in \Omega} \exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)\right]^2} e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu \\ &\quad + \mathbf{1}\{j' = j\} \int \frac{\partial \mu_j(y,\nu)}{\partial p_j} \frac{\exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)}{1 + \sum_{j' \in \Omega} \exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)} e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu \\ &= \frac{1}{p_j} \int \exp(\alpha(y,\nu)) \mathbb{P}_j(y,\nu) \mathbb{P}_{j'}(y,\nu) e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu \\ &\quad - \mathbf{1}\{j' = j\} \frac{1}{p_j} \int \exp(\alpha(y,\nu)) \mathbb{P}_j(y,\nu) e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu \end{aligned}$$

Therefore,

$$\begin{aligned} \frac{p_j}{r_j}\frac{\partial r_{j'}}{\partial p_j} &= \frac{\int \exp(\alpha(y,\nu)) \mathbb{P}_j(y,\nu) \mathbb{P}_{j'}(y,\nu) e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu}{\int \mathbb{P}_j(y,\nu) e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu} \\ &\quad - \mathbf{1}\{j' = j\} \frac{\int \exp(\alpha(y,\nu)) \mathbb{P}_j(y,\nu) e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu}{\int \mathbb{P}_j(y,\nu) e(y) F_y(y) F_\nu(\nu)\, dy\, d\nu} \\ &= \int \exp(\alpha(y,\nu)) \mathbb{P}_{j'}(y,\nu) \omega^{(2)}(y,\nu)\, dy\, d\nu \\ &\quad - \mathbf{1}\{j' = j\} \int \exp(\alpha(y,\nu)) \omega^{(2)}(y,\nu) dy\, d\nu \end{aligned}$$

with $\omega^{(2)}(y,\nu) \equiv \frac{\mathbb{P}_j(y,\nu)e(y)F_y(y)F_\nu(\nu)}{\int \mathbb{P}_j(y,\nu)e(y)F_y(y)F_\nu(\nu) dy\, d\nu}$.

Going back to the first order conditions, we can write the set of conditions for all firms as

$$M - \Delta(1 - M) = 0$$

where M is the vector of inverse multiplicative markup, c_j/p_j, and Δ is the matrix of $-\frac{p_j}{r_j}\frac{\partial r_{j'}}{\partial p_j}$

defined as :

$$\Delta_{j,j'} = \begin{cases} \int (1-\mathbb{P}_j(y,\nu))\,\exp(\alpha(y,\nu))\,\omega_j^{(2)}(y,\nu)\,dyd\nu & \text{if } j=j', \\ -\int \mathbb{P}_{j'}(y,\nu)\,\exp(\alpha(y,\nu))\,\omega_j^{(2)}(y,\nu)\,dyd\nu & \text{if j and j' belong to the same firm,} \\ 0 & \text{otherwise.} \end{cases}$$

In the case of a single product firm, the firm only cares about the diagonal term so that the optimal markup can be written

$$\frac{p_j}{c_j} = \frac{1}{M_j} = 1 + \frac{1}{\Delta_{j,j}} = 1 + \frac{1}{\int (1-\mathbb{P}_j(y,\nu))\,\exp(\alpha(y,\nu))\,\omega_j^{(2)}(y,\nu)\,dyd\nu}.$$

Derivation of the optimal quality Taking the derivative of the profit function with respect to quality, we obtain the following first order conditions

$$\begin{aligned} \frac{\partial \Pi_f}{\partial \lambda_j} = 0\,, \quad \forall j \in F \qquad &\Leftrightarrow \quad -\frac{r_j}{p_j}\frac{\partial c_j}{\partial \lambda_j} + \sum_{j' \in F} \frac{\partial r_{j'}}{\partial \lambda_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0\,, \quad \forall j \in F \\ &\Leftrightarrow \quad -\frac{c_j}{p_j}\frac{\partial \ln c_j}{\partial \lambda_j} + \sum_{j' \in F} \frac{1}{r_j}\frac{\partial r_{j'}}{\partial \lambda_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0\,, \quad \forall j \in F \end{aligned}$$

From the first order conditions on prices, we know that

$$\sum_{j' \in F} \frac{p_j}{r_j}\frac{\partial r_{j'}}{\partial p_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = -\frac{c_j}{p_j}\,, \quad \forall j \in F$$

so that the set of first order conditions with respect to quality λ_j can be written

$$\frac{\partial \ln c_j}{\partial \lambda_j}\sum_{j' \in F} \frac{p_j}{r_j}\frac{\partial r_{j'}}{\partial p_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) + \sum_{j' \in F} \frac{1}{r_j}\frac{\partial r_{j'}}{\partial \lambda_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right) = 0\,, \quad \forall j \in F$$

which implies

$$\begin{aligned} \frac{\partial \ln c_j}{\partial \lambda_j} &= -\frac{\sum_{j' \in F} \frac{1}{r_j}\frac{\partial r_{j'}}{\partial \lambda_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right)}{\sum_{j' \in F} \frac{p_j}{r_j}\frac{\partial r_{j'}}{\partial p_j}\left(1 - \frac{c_{j'}}{p_{j'}}\right)}\,, \quad \forall j \in F \\ \frac{\partial \ln c_j}{\partial \lambda_j} &= \frac{G_{(j)}(1-M)}{\Delta_{(j)}(1-M)}\,, \quad \forall j \in \Omega \end{aligned}$$

where $\Delta_{(j)}$ and $G_{(j)}$ are respectively the j-th row of matrices Δ and G, and G is defined as follows.

$$\begin{aligned}
G_{(j,j)} = \frac{1}{r_j}\frac{\partial r_j}{\partial \lambda_j} &= \frac{1}{r_j}\frac{\partial}{\partial \lambda_j}\left\{\int \frac{\exp\left(\delta_j + \mu_j(y,\nu)\right)}{1+\sum_{j'\in\Omega}\exp\left(\delta_{j'}+\mu_{j'}(y,\nu)\right)} e(y)F_y(y)F_\nu(\nu)\,dy\,d\nu\right\} \\
&= \frac{1}{r_j}\int \mathbb{P}_j(y,\nu)(1-\mathbb{P}_j(y,\nu))e(y)F_y(y)F_\nu(\nu)\,dy\,d\nu \\
&= \int (1-\mathbb{P}_j(y,\nu))\,\omega^{(2)}(y,\nu)\,dy\,d\nu \\
G_{(j,j')} = \frac{1}{r_j}\frac{\partial r_{j'}}{\partial \lambda_j} &= \frac{1}{r_j}\frac{\partial}{\partial \lambda_j}\left\{\int \frac{\exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)}{1+\sum_{j'\in\Omega}\exp\left(\delta_{j'}+\mu_{j'}(y,\nu)\right)} e(y)F_y(y)F_\nu(\nu)\,dy\,d\nu\right\} \\
&= -\frac{1}{r_j}\int \mathbb{P}_j(y,\nu)\mathbb{P}_{j'}(y,\nu)e(y)F_y(y)F_\nu(\nu)\,dy\,d\nu \\
&= -\int \mathbb{P}_{j'}(y,\nu)\,\omega^{(2)}(y,\nu)\,dy\,d\nu \quad \text{if } j \text{ and } j' \text{ belong to the same firm,} \\
G_{(j,j')} = 0 & \qquad \text{if } j \text{ and } j' \text{ do not belong to the same firm.}
\end{aligned}$$

In the case of a single product firm, only the diagonal terms of these matrices matter so that the first order condition becomes:

$$\begin{aligned}
&\frac{\partial \ln c_j}{\partial \lambda_j} = \frac{G_{(j,j)}(1-\frac{c_j}{p_j})}{\Delta_{(j,j)}(1-\frac{c_j}{p_j})} \\
\Leftrightarrow\quad &\frac{\partial \ln c_j}{\partial \lambda_j} = \frac{\int(1-\mathbb{P}_{j'}(y,\nu))\,\omega^{(2)}(y,\nu)\,dy\,d\nu}{\int(1-\mathbb{P}_j(y,\nu))\,\exp(\alpha(y,\nu))\,\omega_j^{(2)}(y,\nu)\,dyd\nu} = \frac{1}{\int\exp(\alpha(y,\nu))\,\omega_j^{(3)}(y,\nu)\,dyd\nu}
\end{aligned}$$

with $\omega^{(3)}(y,\nu) \equiv \frac{\mathbb{P}_j(y,\nu)(1-\mathbb{P}_j(y,\nu))e(y)F_y(y)F_\nu(\nu)}{\int \mathbb{P}_j(y,\nu)(1-\mathbb{P}_j(y,\nu))e(y)F_y(y)F_\nu(\nu)dy\,d\nu}$.

Derivations for the counterfactual experiment In the counterfactual experiment of section 6, we derive an alternative equilibrium without solving for the fundamentals introduced in the supply side of the model (the productivity φ_{jdt} and the cost-elasticity of quality η_{jdt}). The reason for this feature is that we solve the model from an initial equilibrium that satisfies the first order conditions imposed in our counterfactual experiment. In this section, we detail the steps that allows us to define the new equilibrium from the initial one.

First, the first order condition on quality (12) is

$$\lambda_{jdt} = \frac{1}{2h}\left((\tilde{\alpha}_{jdt})^{-1} - \eta_{jdt}\right)$$

so that we can obtain the new optimal quality $\lambda_{jdt}^{(s)}$ at iteration s from the initial $\lambda_{jdt}^{(0)}$ as follows:

$$\lambda_{jdt}^{(s)} = \lambda_{jdt}^{(0)} + \frac{1}{2h}\left(\left(\tilde{\alpha}_{jdt}^{(s)}\right)^{-1} - \left(\tilde{\alpha}_{jdt}^{(0)}\right)^{-1}\right),$$

avoiding to solve for the variety-specific cost-elasticity of quality η_{jdt}.

Similarly, the marginal cost function (7) is defined as

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

so that we can write

$$\begin{aligned}
\ln c_{jdt}^{(s)} &= \ln c_{jdt}^{(0)} + \eta_{jdt}\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right) + h\left({\lambda_{jdt}^{(s)}}^2 - {\lambda_{jdt}^{(0)}}^2\right) \\
&= \ln c_{jdt}^{(0)} + \eta_{jdt}\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right) + h\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right)\left(\lambda_{jdt}^{(s)} + \lambda_{jdt}^{(0)}\right) \\
&= \ln c_{jdt}^{(0)} + \left(\eta_{jdt} + h\left(\lambda_{jdt}^{(s)} + \lambda_{jdt}^{(0)}\right)\right)\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right)
\end{aligned}$$

Using the first order condition for the initial quality, we have

$$\begin{aligned}
\ln c_{jdt}^{(s)} &= \ln c_{jdt}^{(0)} + \left(\left(\tilde{\alpha}_{jdt}^{(0)}\right)^{-1} - 2h\lambda_{jdt}^{(0)} + h\left(\lambda_{jdt}^{(s)} + \lambda_{jdt}^{(0)}\right)\right)\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right) \\
&= \ln c_{jdt}^{(0)} + \left(\left(\tilde{\alpha}_{jdt}^{(0)}\right)^{-1} + h\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right)\right)\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right) \\
&= \ln c_{jdt}^{(0)} + \left(\tilde{\alpha}_{jdt}^{(0)}\right)^{-1}\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right) + h\left(\lambda_{jdt}^{(s)} - \lambda_{jdt}^{(0)}\right)^2
\end{aligned}$$

which is the relationship we use to update the marginal cost at iteration s given the new optimal quality and the initial equilibrium.

B 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 do not observe prices in 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.

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			

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

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

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

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

In order to make 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,[48] we replace missing weights by applying the conversion rate to supplementary units. It is only after this operation is completed that we aggregate the French customs data first from CN8 to HS6 and then to HS6+, as described in previous paragraph "Harmonization of product codes".

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

[48] 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 products 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.

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 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:

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

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

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

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.

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, fur-skin, 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				

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

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

C Estimation Summary

This appendix summarizes the main estimation steps.

Step 1: Demand side estimation

We estimate non-linear parameters $\theta \equiv \{\alpha, \Pi, \Sigma\}$ by GMM. This procedure also delivers an estimate of linear parameters β and δ_{jdt}. Parameters α, Π and Σ govern the distribution of random coefficients, as defined in equation (3). δ_{jdt}, the mean valuation of variety j by consumers from market dt, is defined in equation (2).

Data Requirements For each variety j and each destination-year market dt, our estimation requires to observe the market share S_{jdt}, product characteristics x_j, normalized log price $\ln p_{jdt} - \ln p_{0dt}$ and a set of instruments Z_{jdt}. In our application, x contains four dummy variables (Leather Sole, Leather top, Fabric top, Boot) and p_{0dt} is the price of the domestic variety. Moreover, in our preferred specification with random coefficients on all characteristics, Z contains 25 instruments:

- **Product Characteristics (4 instruments):** Leather Sole, Leather top, Fabric top, Boot.
- **Cost shifters (3 instruments):** tariff to destination, exchange rate to destination, firm-level import weighted exchange rate.
- **Differentiation IV's (10 instruments):** the log number of French and non-French competitors within one standard deviation in terms of (predicted) log prices.[49] The log number of French and non-French competitors with the same product characteristics.
- **Interactions (8 instruments):** an interaction between a French dummy and the average income on the destination, an interaction between each cost shifter and the average income on the destination, and an interaction between eahc product characteristic and income in the destination.

Algorithm The estimation algorithm consists in iterating over θ. Each iteration has three steps:

1. Solve for $\delta(S, x, \ln p; \theta^{(k)})$ by iterating over contraction mapping

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

where

$$s_{jdt}(\delta, x, \ln p; \theta) \equiv \int \frac{\exp\left(\delta_{jdt} + \mu(y, \nu; x_j, \ln p_{jdt}, \theta)\right)}{1 + \sum_{j' \in \Omega_{dt}} \exp\left(\delta_{j'dt} + \mu(y, \nu; x_{j'}, \ln p_{j'dt}, \theta)\right)} \omega^{(1)}_{jdt}(y, \nu)\, dy\, d\nu,$$

[49] Predicted log prices are obtained by regressing log prices on cost shifters, product characteristics and producer dummies.

and $\omega^{(1)}(y,\nu) \equiv \frac{e(y)\,F_y(y)\,F_\nu(\nu)}{\int e(y)\,F_{y,d}(y)\,F_\nu(\nu)\,dy\,d\nu}$. $F_{y,d}$ is the density function of log-income in destination d. F_ν is the standard normal density function. Moreover, $\mu(y,\nu;x_j,\ln p_j,\theta) \equiv x_j(\beta(y,\nu)-\beta) - \exp(\alpha(y,\nu))(\ln p_j - \ln p_0)$, with

$$\begin{bmatrix}\alpha(y,\nu)\\ \beta(y,\nu)\end{bmatrix} \equiv \begin{pmatrix}\alpha\\ \beta\end{pmatrix} + \Pi y + \Sigma\nu$$

Iteration stops when the minimum of the vector of squared difference between $\delta^{(h+1)}$ and $\delta^{(h)}$ is less than 10^{-12}. The convergence of the contraction mapping is accelerated using the Squarem acceleration method developed in Varadhan and Roland (2004). Moreover, we numerically approximate the integrals involved in the computation of $s(\delta^{(h)},x,\ln p;\theta)$ with 500 draws from Halton sequences. A draw is a vector of 7 numbers from a normal distribution so that we can approximate the distribution of income as well as the random preferences for the 6 observed characteristics.

2. Using OLS, regress $\delta(S,x,\ln p;\theta)$ on product characteristics x and producer dummies γ :

$$\delta_{jdt}(S,x,\ln p;\theta) = x_j\beta + \gamma_f + \xi_{jdt},$$

and collect the structural errors:

$$\hat{\xi}_{jdt}(\theta) = \delta_{jdt}(S,x,\ln p;\theta) - x_j\hat{\beta} - \hat{\gamma}_f - \widehat{\log n}(Z_{Jdt})$$

where $\widehat{\log n}(Z_{Jdt})$ is the predicted log number of foreign varieties. We construct this control function by regressing $\log n_{Fpdt}$, the number of French varieties exported to destination d at time t, on our sets of instruments Z, destination and year dummies. We then constructed the predicted value $\widehat{\log n}(Z_{Jdt})$ from this regression for each foreign variety.

3. Pick a new value $\theta^{(k+1)}$ so as to minimize objective function

$$\hat{\xi}(\theta)'Z\Phi Z'\hat{\xi}(\theta),$$

with Φ the weighting matrix $\Phi = (Z'Z)^{-1}$ and Z the vector of instruments.

Standard Errors We obtain the GMM standard errors for estimator $\hat{\theta}$ from Newey and McFadden (1994):

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

where G is the gradient of the objective function and $\hat{\Lambda}$ is the estimator of the covariance matrix of the vector of moments, taking into account the panel structure of the data. Specifically, we have

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

where C is the total number of producers (firm or country) and i denotes an observation. To minimize the GMM objective function, we employ the "Trust-region" algorithm in Matlab, to which we provide the analytical gradient of the objective function.

Step 2: Demand side post-estimation

As a by-product of step 1 , we back out

- quality estimates from $\lambda_{jdt} = \delta_{jdt} - \beta x_j$
- estimates of markup, using the first-order condition on prices:

$$M - \Delta(1 - M) = 0$$

where M is the vector of the inverse multiplicative markups on a destination market, $M_j \equiv \frac{c_j}{p_j}$, and Δ the matrix defined as

$$\Delta_{j,j'} = \begin{cases} \int (1 - \mathbb{P}_j(y,\nu)) \exp(\alpha(y,\nu))\, \omega_j^{(2)}(y,\nu)\, dy d\nu & \text{if } j = j', \\ -\int \mathbb{P}_{j'}(y,\nu) \exp(\alpha(y,\nu))\, \omega_j^{(2)}(y,\nu)\, dy d\nu & \text{if } j \text{ and } j' \text{ belong to the same firm,} \\ 0 & \text{otherwise,} \end{cases}$$

with $\omega_j^{(2)}(y,\nu) \equiv \frac{e(y)\mathbb{P}_j(y,\nu)F_y(y)F_\nu(\nu)}{\int e(y)\mathbb{P}_j(y,\nu)F_y(y)F_\nu(\nu)dyd\nu}$ and

$$\mathbb{P}_j(y,\nu) = \frac{\exp(\delta_j + \mu_j(y,\nu))}{1 + \sum_{j' \in \Omega} \exp\left(\delta_{j'} + \mu_{j'}(y,\nu)\right)}.$$

- marginal cost estimates from identity $\ln c_{jdt} = \ln p_{jdt} + \ln M_{jdt}$
- estimates of the average own-price elasticity $\tilde{\alpha}_{jdt}$ from equation:

$$\tilde{\alpha}_j \equiv \frac{\Delta_{(j)}(1-M)}{G_{(j)}(1-M)},$$

with $\Delta_{(j)}$ and $G_{(j)}$ respectively the j-th row of Δ and G.

Step 3: Supply side estimation

In this step, we recover three different estimates of h, the parameter driving the curvature of the cost-quality relationship

1. The first estimate of h is obtained through a regression of quality λ_{jdt} on $\tilde{\alpha}_j^{-1}$ in first differences:

$$\Delta\lambda_{jdt} = \beta_1 \Delta\tilde{\alpha}_{jdt}^{-1} + \gamma_{dt} + \varepsilon_{jdt}.$$

We know from the first order condition on quality that $\beta_1 = \frac{1}{2h}$. Therefore an estimator of h is $\hat{h} = \frac{1}{2\hat{\beta}_1}$. Coefficient $\hat{\beta}_1$ is obtained by 2SLS. The instrumental variable is $\Delta instr_{jdt}$

with

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

where δ_{jd0} and μ_{jd0} denote the initial δ and μ of producer j in destination d.

2. The second estimate of h is obtained through a regression of the logarithm of marginal costs $\ln c_{jdt}$ on $\frac{\left(\tilde{\alpha}_{jdt}^{-1}\right)^2}{2}$:

$$
\Delta \ln c_{jdt} = \beta_1 \Delta \frac{\left(\tilde{\alpha}_{jdt}^{-1}\right)^2}{2} + \gamma_{dt} + \varepsilon_{jdt}.
$$

   By dividing by two our variables of interest, we know from the first order condition on quality and the marginal cost equation that $\beta_1 = \frac{1}{2h}$. Therefore an estimator of h is $\hat{h} = \frac{1}{2\hat{\beta}_1}$. Coefficient $\hat{\beta}_1$ is obtained by 2SLS, using $\Delta instr_{jdt}^2$ as instrument.

3. Finally, we perform a stacked regression by combining both estimation equations from above. The left-hand side variable consists of the first difference of quality and the first difference in the log of marginal costs, which we regress on a column made of $\Delta\tilde{\alpha}_{jdt}^{-1}$ stacked over $\Delta\frac{\left(\tilde{\alpha}_{jdt}^{-1}\right)^2}{2}$ and two sets of destination-year fixed effects (one for each variable). Moreover, we use the same instruments described in the first two strategies. This allows us to obtain a consistent estimate for $\frac{1}{2h}$, combining both sources of identification.

D Accounting for Hidden Varieties

The empirical analysis carried out in this paper combines firm-level data for French exports and country-level data for non-French exports. The fact that we do not observe the entirety of trade at the micro level raises the concern that our parameter estimates and counterfactual results may suffer from an aggregation bias. In this appendix, we investigate this possibility by simulating the existence of several producers from each origin countries, located at different points in the price distribution. While the creation of this simulated dataset is not equivalent to having access to the true distribution of exporters from all foreign countries, it allows us to assess the sensitivity of our results to a potential aggregation bias.

In order to disaggregate country-level data into individual producers, we split any country-destination-product-year trade flow $cdpt$ into five firm-level trade flows $fcdpt$ of equal size. To assign different prices to each observation, we assume that these log-prices are normally distributed around the aggregated log-price. Specifically, we set four prices at the 20th, 40th, 60th and 80th percentile of the normal distribution using the standard deviation of prices from French firm-level data.[50] Then, we set the price of the fifth observation so that the prices of these individual observations aggregate to the observed aggregate price in the original data.

Table 8 reports the estimation results using the initial sample with aggregate data, and the newly created sample with simulated foreign firms. Most of the estimated parameters are consistent across samples: in both samples, we find an average price-elasticity around 2.5, a negative impact of income on this elasticity, as well as some additional variations in price-elasticity based on unobservables. Moreover, we do see that in both cases, French varieties are closer substitutes relative to foreign varieties. The only coefficients that differ across samples are the ones related to the variable "Leather Sole", but this is mostly driven by very large standard errors. Overall, this suggests that our baseline estimates do not suffer from a large aggregation bias.

In addition to being a potential issue for our estimation, the presence of hidden varieties also matters for our counterfactual experiment. The presence of different Chinese exporters, which differ in prices, implies that our aggregate data does not allow us to capture the correct effect on French firms. To assess the extent to which this might affect our counterfactual results, we rerun this experiment by using once again a set of simulated firms. Using the estimates from table 8, we run our experiment assuming that the fundamentals of all Chinese firms are brought to their post-2007 values. Figure 16 reports the results of our counterfactual experiment in that context.

Once again, we find little difference between these results and the ones using the aggregated sample reported in figure 9. We still find that French firms are differently affected by Chinese competition, and that quality upgrading helps low-price French firms at mitigating this adverse shock to a limited extent. This is reassuring that the absence of disaggregated data does not strongly affect the conclusions of our paper.

[50] We compute the standard deviation of log prices among French firms, separately on each market dpt. Then, we obtain σ by averaging this standard deviation across markets.

Table 8: Estimation results across samples

	Initial sample			**Disaggregated sample**		
	Mean	Π	Σ	Mean	Π	Σ
α	0.89^{***}	-0.58^{***}	0.40	1.26^{***}	-0.39^{***}	0.37^{*}
	(0.18)	(0.19)	(0.36)	(0.36)	(0.17)	(0.22)
French	.	-0.25	4.71^{***}	.	-0.20	5.78^{***}
		(0.35)	(0.42)		(0.54)	(1.46)
Leather sole	-0.89	-0.43^{**}	-0.50	-21.06^{**}	1.64	14.79^{***}
	(1.80)	(0.18)	(4.72)	(10.37)	(1.08)	(6.69)
Leather top	0.26^{*}	0.83^{***}	0.069	0.27	0.98^{*}	1.48
	(0.14)	(0.22)	(1.30)	(0.25)	(0.57)	(1.35)
Fabric top	-0.93	1.09^{***}	-0.76	-1.01^{**}	0.85^{***}	0.05
	(2.89)	(0.26)	(5.85)	(0.45)	(0.27)	(2.31)
Boot	-0.33^{**}	0.091	-0.54	-0.26^{***}	-0.01	-0.29
	(0.16)	(0.11)	(0.72)	(0.09)	(0.13)	(0.39)
N		193 927			555 123	

Notes: Standard errors between parentheses clustered at the country level. All specifications include firm fixed effects and implement our control function. Instruments in both specifications are product characteristics, the three cost shifters, the logarithm of the number of predicted prices within one standard deviation, the logarithm of the number of French predicted prices within one standard deviation, the number of competitors and French competitors with the same product characteristics, interactions between the cost shifters, a French dummy, product characteristics and the average income in the destination market (total of 25 instruments). Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

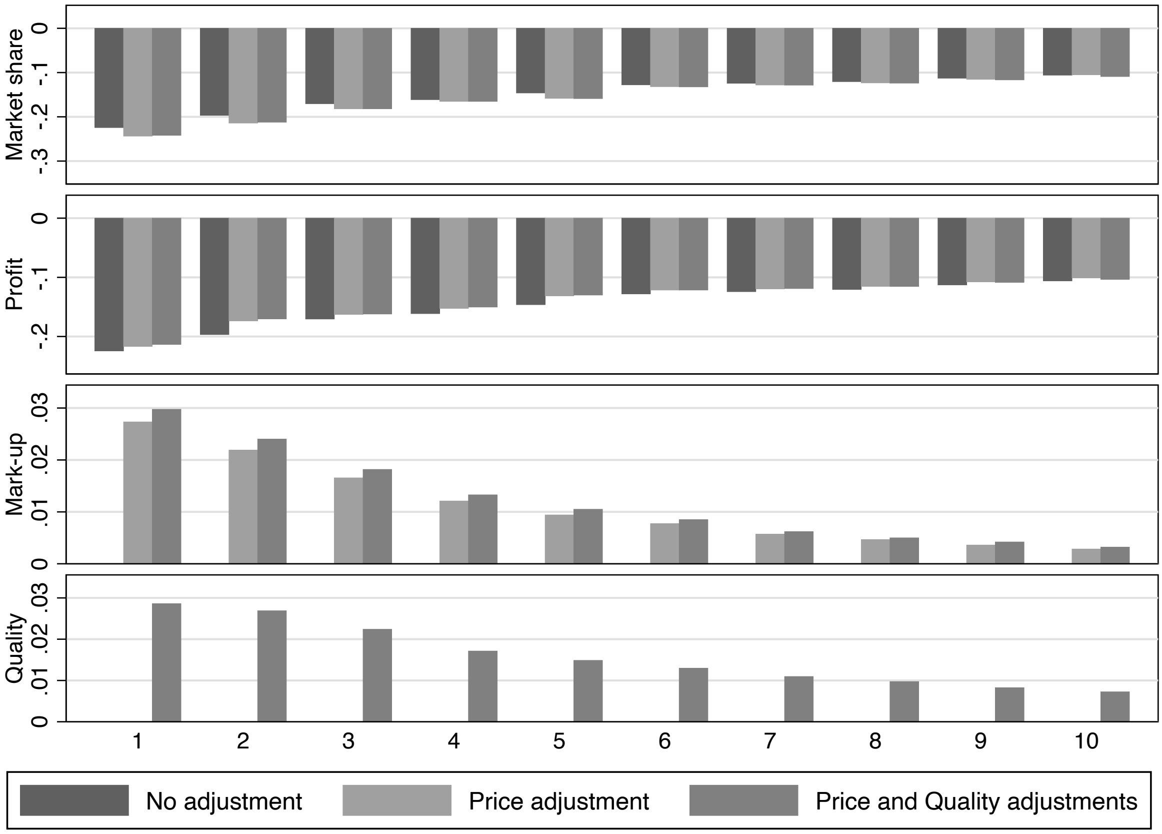

FIGURE 11: Effect of the China shock (disaggregated data)

Notes: The figure reports the median log-change in market shares for all French firms in 1997, separately for each price decile. The change is measured between the true scenario and the counterfactual scenario in which China increases its fundamentals to their post 2007 levels.

E Additional Results

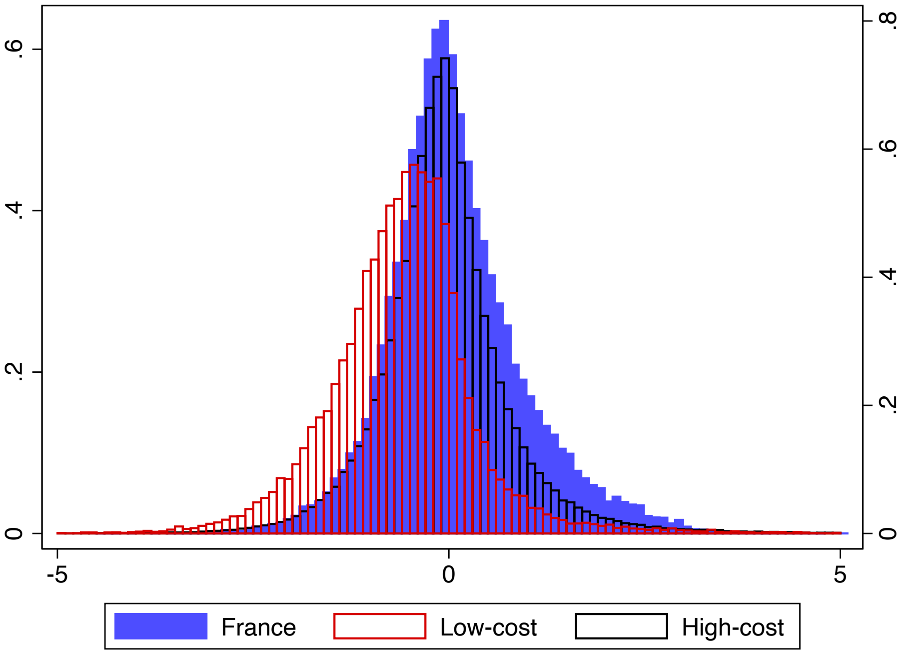

FIGURE 12: Distribution of Export prices

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.

TABLE 9: Control function estimation

	Log (n varieties)	
Log tariff	-0.75	-0.75
	(0.97)	(0.88)
Log exchange rate	-0.22***	-0.22***
	(0.067)	(0.061)
Sole Leather	-0.59***	
	(0.019)	
Top Leather	0.90***	
	(0.025)	
Top Fabric	0.33***	
	(0.028)	
Boot	-0.54***	
	(0.020)	
N	1736	1736
R^2	0.82	0.86
Year FE	Y	Y
Destination FE	Y	Y
Product FE	N	Y

Notes: Standard errors in parentheses. Estimation on French customs data. Significance levels: *** p<0.01.

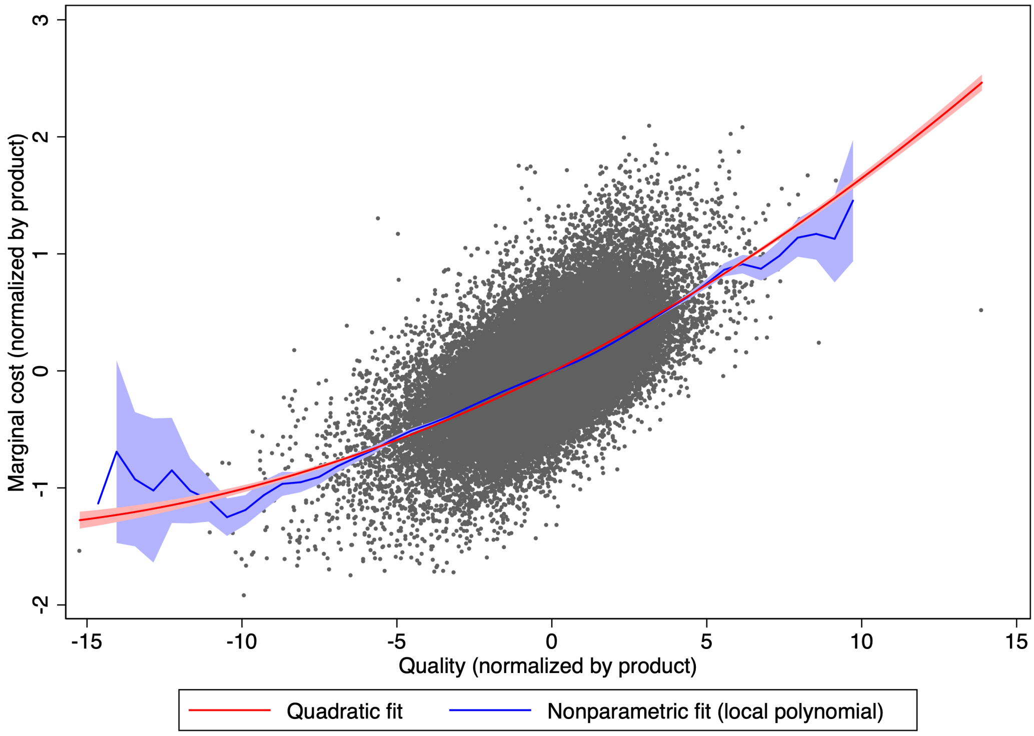

FIGURE 13: Relationship between marginal cost and product quality

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

Table 10: Estimation results with product dummies

	OLS	2SLS	Random coefficients		
	(1)	(2)	(3)		
			Mean	Π	Σ
log price	0.20^{***}	-1.91^{***}			
	(0.056)	(0.24)			
log price $\times$ inc_d	0.41^{***}	0.74^{***}			
	(0.054)	(0.22)			
α			1.08^{***}	-0.45^{***}	-0.36^{*}
			(0.11)	(0.10)	(0.19)
$French$			.	0.13	5.04^{***}
				(0.27)	(0.24)
Control function	No	No	Yes		
R^2	0.55				
First stage F-stat		34.3			

Notes: Number of observations: 193 927. Standard errors between parentheses clustered at the producer level. All specifications include producer (firm or country) and product fixed effects. Instruments for specification (2) are the three cost shifters and their interaction with the destination log average income. Specification (3) uses the following instruments: product dummies, the three cost shifters, the logarithm of the number of predicted prices within one standard deviation, the logarithm of the number of French predicted prices within one standard deviation, and an interaction between the cost shifters, a French dummy and the average income on the destination (total of 13 instruments). Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

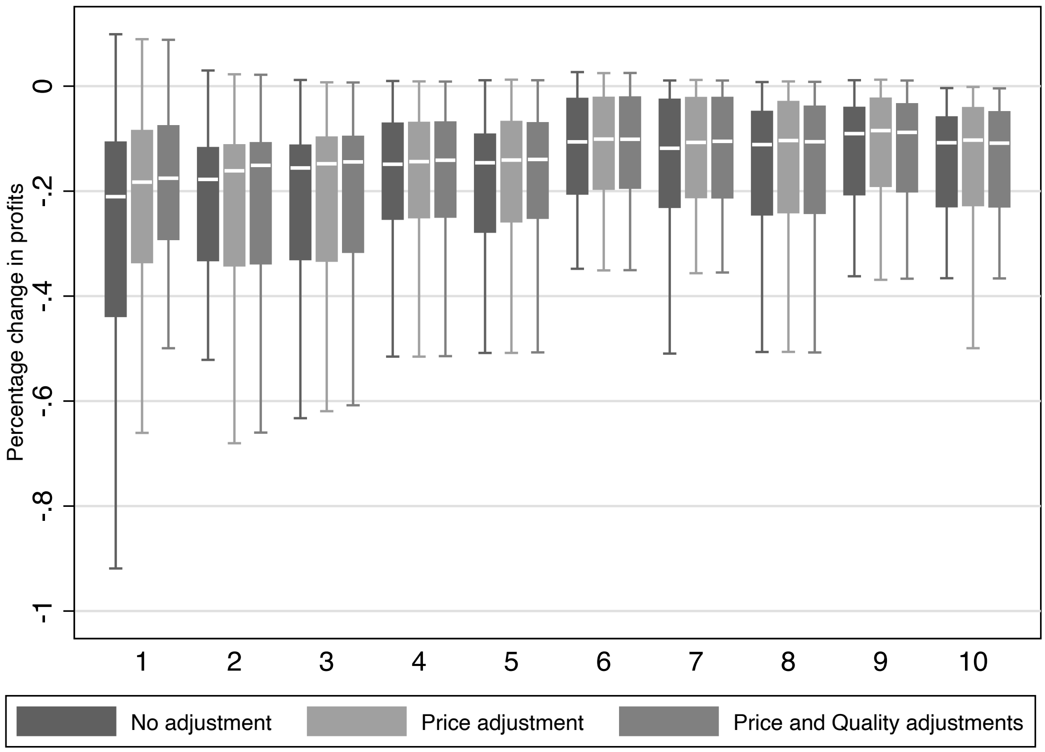

FIGURE 14: Distribution of the effect of the China shock on market shares by price deciles (on French firms in 1997). Observations within price deciles vary across firms and destinations: because some destinations see a decrease in Chinese competition for some products, the experiment increases the market shares of some French varieties.

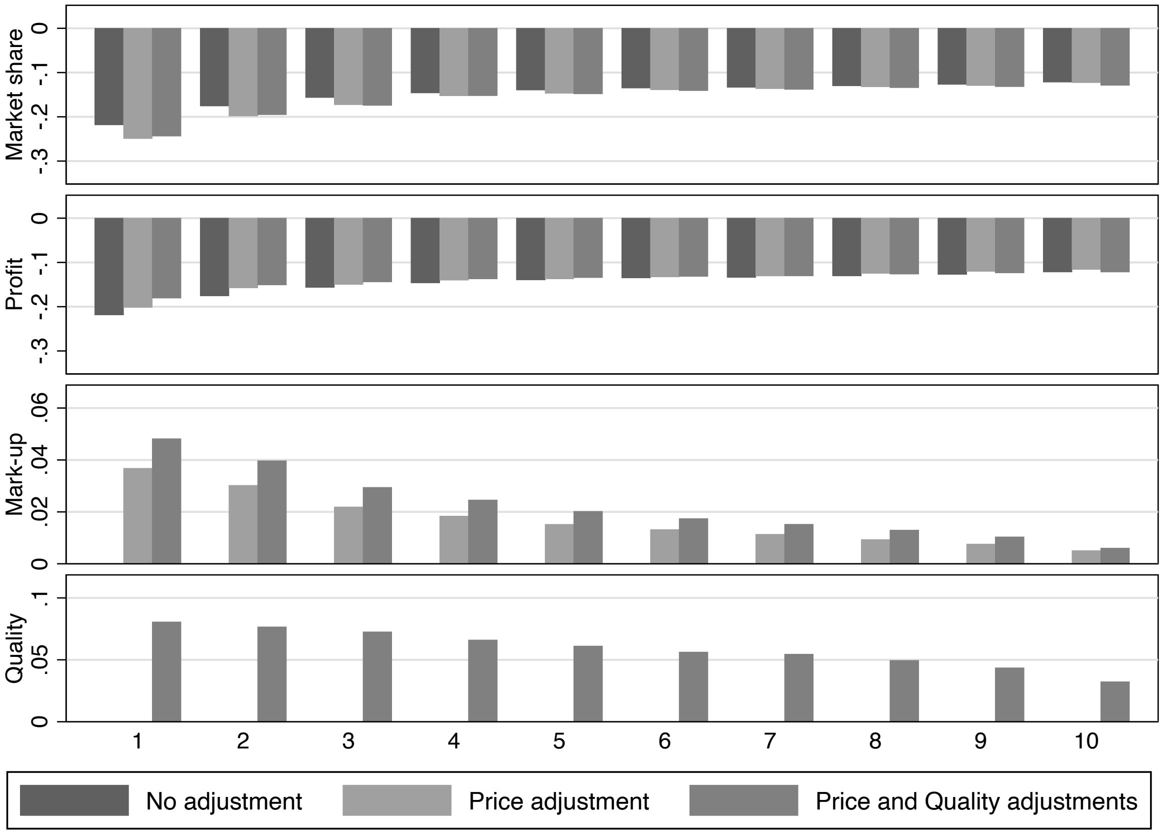

FIGURE 15: Effect of the China shock and the quality response with $h = 0.16$

Notes: The figure reports the median log-change in market shares for all French firms in 1997, separately for each price decile. The change is measured between the true scenario and the counterfactual scenario in which China increases its fundamentals to their post 2007 levels.

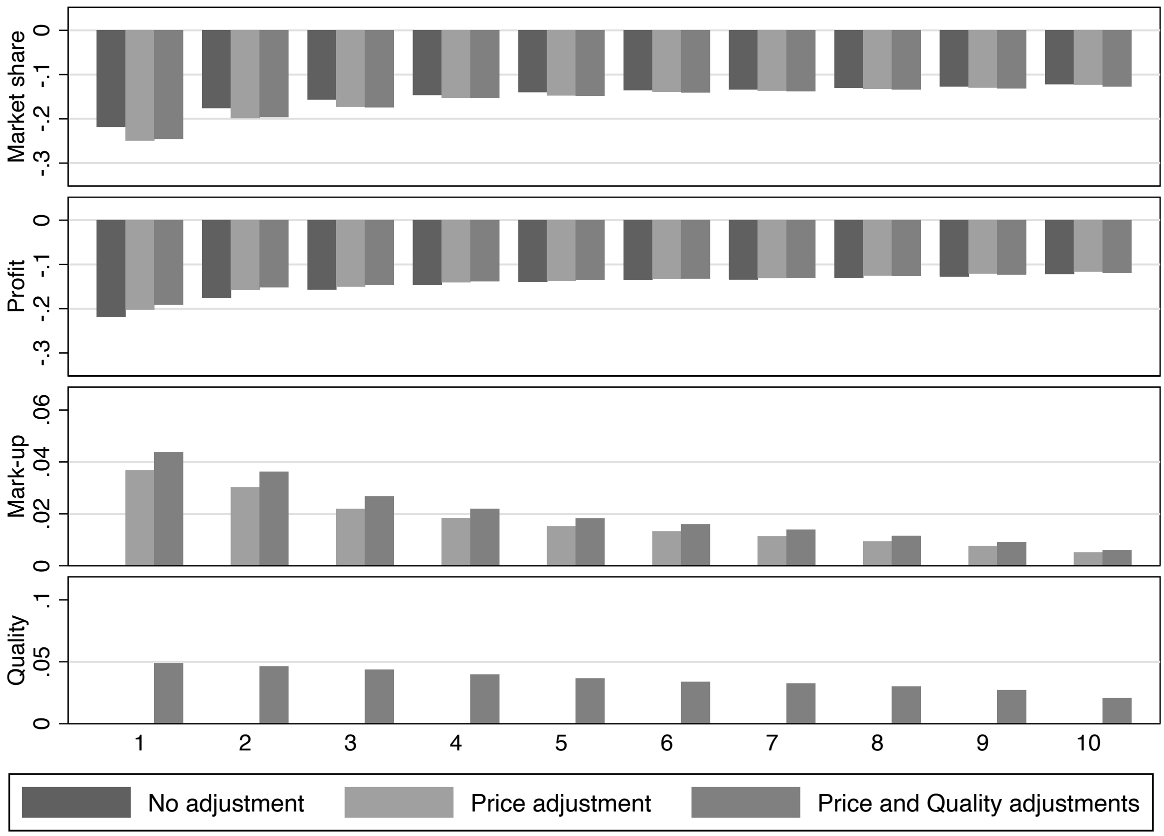

FIGURE 16: Effect of the China shock and the quality response with $h = 0.24$

Notes: The figure reports the median log-change in market shares for all French firms in 1997, separately for each price decile. The change is measured between the true scenario and the counterfactual scenario in which China increases its fundamentals to their post 2007 levels.