Foreign Competition along the Quality Ladder*

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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 significantly more damaging to French firms at the bottom of the price distribution, and that quality upgrading had a limited role at mitigating the heterogenous impact of the shock.

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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 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 choices 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 had a limited role at mitigating the effects of low-cost competition.

Using our estimated model to simulate the effects of the "China shock", we find that low-cost varieties from developed economies suffered significantly more from Chinese competition than expensive ones. This heterogeneity comes from horizontal differentiation – within an industry, some product categories are more exposed to Chinese competition – but also from vertical differentiation: within a product category, low-cost varieties are more directly impacted by China. In the case of the footwear industry, we find that one third of the differentiated impact between low prices and high prices comes from vertical differentiation. By contrast, a model without heterogeneity in price elasticity would have totally muted this channel. Our results thus underline the importance of taking into account consumer heterogeneity to measure the effects of foreign competition.

We start our analysis 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 such that French exporters appears more affected

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

by competing firms that resemble them. Moreover, we find that increasing low-cost competition is also associated with price adjustments: firms with low prices, which are more affected by low-cost competition, increase their price relative to high price firms when low-cost competition intensifies.

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 develop a random-coefficients nested logit (RCNL) model to introduce heterogeneity and a nested structure in consumers preferences.[2] The presence of nests in preferences naturally accommodates the existence of product categories and countries of origin in the trade data and allows us to estimate specific substitution patterns between varieties in the same category or from the same origin. Moreover, 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 consequence, 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.[3] 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 to

[2] See Brenkers and Verboven (2006) for the first paper introducing the RCNL.

[3] 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.

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, we can capture heterogeneity in preferences from variations in income distributions across destination markets.

The demand estimation results confirm the existence of heterogeneity in consumers' preferences. We find that the product nests play an important role so that products belonging to the same product category or from the same origin country are much more substitutable. Moreover, we find significant heterogeneity in price-elasticity, in particular related to the income of the consumer: 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. We also 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 with varieties from low-cost countries. These firms sell cheap products and thus compete for the same consumers as Chinese varieties. As a consequence, their sales are highly sensitive to Chinese prices.

The estimation 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. To circumvent this endogeneity problem, we estimate the change in quality and marginal costs generated by a change in competition only, holding characteristics of the firm constant: 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 a variable 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 quality 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 empirical 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 in our counterfactual experiments, 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 the market share of firms located at the bottom decile of the price distribution decrease by an additional 8 percent relative to firms producing similar varieties but located in the top decile. When comparing horizontal and vertical differentiation, we find that the latter is as important as half of the former to explain the heterogenous impact of Chinese competition along the quality ladder.[4] Moreover, we find that the ability of firms to upgrade the quality of their product can mitigate part of the dispersion in the effect of the China shock: roughly one third of the heterogenous effect is reduced when firms that are particularly exposed, located at the bottom of the price distribution, escape this increasing competition by moving up the quality ladder. However, the large costs associated with producing higher quality prevent them from fully absorbing the adverse effect of the shock, leaving significant heterogeneity along the quality ladder.

The empirical model in this paper borrows from demand systems developed in industrial organization. Berry, Levinsohn, and Pakes (1995) is the seminal paper that introduces random coefficients in demand estimation. Brenkers and Verboven (2006) and Grigolon and Verboven (2014) develop a similar RCNL that the one used in our paper, which allows us to combine random coefficients on prices and nested logit utility terms on discrete categories. More recently, Head and Mayer (2019) study the importance of random-coefficients demand system in international trade, by comparing the performance of CES or Nested logit models relative to random-coefficients models.[5] They show that models without random coefficients can be a reasonable approximation when studying the consequences of a trade liberalization episode. However, in the context of our paper, models without random coefficients cannot explain any differentiated impact of competition along the quality ladder within a narrowly defined market.

Our work relates to the literature estimating firm product quality using microeconomic data. Roberts, Xu, Fan, and Zhang (2017) and Hottman, Redding, and Weinstein (2016) estimate demand functions respectively using firm level and barcode level data to disentangle price-competitiveness from non-price competitiveness in the dispersion of firms' performance.[6] 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

[4]We find that within a destination market, the nested logit model, capturing horizontal differentiation, can explain two third of the heterogeneous impact of the China shock along the price distribution. However, within a destination-HS6 market, the nested logit model cannot predict any differentiated impact, unlike the RCNL model.

[5]See also Goldberg (1995) and Goldberg and Verboven (2001) for papers implementing nested logit models on international trade data.

[6]See Hallak and Schott (2011) or Feenstra and Romalis (2014) for similar studies at a more aggregated 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 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.[7] The information is disaggregated at the firm, year, destination (or origin) country and eight-digit product category of the combined nomenclature (CN8).[8] 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 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.[9] We

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

[8] 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.

[9] 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.

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.

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. 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.[10] Moreover, since the empirical model will require information about destination markets, we limit our sample to 38 destinations from the World Input-Output Database (WIOD).[11]

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 each firm-HS6-destination triplet fpd in the first years of the sample, and relative to the average price in its own destination-HS6 market. Specifically, we project the logarithm of the unit value of each French firm before 2001 on a set of firm-HS6-destination and HS6-destination-year fixed effects:[12]

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

so that the fixed effect γ_{fpd} measures the position of variety fpd in the local price distribution. From this measure, we construct the price quartiles PQ_{fpd}, which correspond to the quartile rank of γ_{fpd} in the distribution of market 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,[13] and estimate how individual exporters are

[10] 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.

[11] 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.

[12] 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 year of observation.

[13] We classify as "low-cost", countries that belong to the low or middle-low income group from the World Bank.

differently affected by the change in this market share. Specifically, we estimate the following regression:

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

where Y_{fdpt} is a measure of export performance, either the logarithm of export values, the logarithm of export prices 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 along 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.

Low-cost competition and firm-level French exports We report the results of these regressions in table 1.[14] In column (1), we only include a market-year fixed effect γ_{pdt}, 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 high 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 share of low-cost countries is associated with a 2 percent larger decrease in the export value of low-price varieties.[15]

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

Overall, table 1 suggests that low-price varieties are in closer competition to products from

See table 8 in appendix B for details.

[14]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.

[15]In table 9 of appendix D, we show that similar patterns holds when looking at the impact of Chinese competition only.

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

Dependent variable:	*log export*		*Survival*	
	(1)	(2)	(3)	(4)
2nd price quartile	-0.17***	.	0.011***	.
	(0.01)		(0.0008)	
3rd price quartile	-0.27***	.	0.020***	.
	(0.010)		(0.0008)	
4th price quartile	-0.22***	.	0.0021**	.
	(0.009)		(0.0007)	
Low-cost penetration				
× 2nd price quartile	0.53***	0.16***	0.035***	0.078***
	(0.04)	(0.04)	(0.004)	(0.009)
× 3rd price quartile	0.82***	0.22***	0.041***	0.11***
	(0.04)	(0.04)	(0.004)	(0.009)
× 4th price quartile	1.15***	0.18***	0.067***	0.13***
	(0.04)	(0.04)	(0.004)	(0.009)
N	6 408 472	6 268 551	6 172 096	6 045 454
R^2	0.29	0.83	0.14	0.40
Year × Prod × Dest FE	Y	Y	Y	Y
Firm × Prod × Dest FE	N	Y	N	Y

Notes: Standard errors clustered at the firm-destination-product level between parentheses. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

low-wage countries than high-price varieties. However, a potential alternative explanation for these results could be that low-price firms are simply less resilient to any type of competition, and not specifically to low-cost competition. To show that the lesser resilience of low-price firms is specific to low-cost competition, we re-run the same regressions as in table 1 but looking at the effect of competition from high-cost countries.[16] 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).

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 10 in the appendix D 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.

Low-cost competition and the price of French varieties In table 3, we look at the differential effect of low-cost competition on prices. We find that stronger low-cost competition is also associated with an increase in the relative price of cheaper varieties. In particular, column (2) shows that low-price French firms increase their export price, relative to firms with higher

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

TABLE 2: High-price varieties suffer more from high-cost competition

Dependent variable:	*log export* (1)	(2)	*Survival* (3)	(4)
2nd price quartile	0.029	.	0.028***	.
	(0.02)		(0.002)	
3rd price quartile	-0.010	.	0.036***	.
	(0.02)		(0.002)	
4th price quartile	0.16***	.	0.042***	.
	(0.02)		(0.002)	
High-cost penetration				
× 2nd price quartile	-0.20***	-0.074*	-0.019***	-0.046***
	(0.03)	(0.03)	(0.003)	(0.007)
× 3rd price quartile	-0.25***	0.045	-0.017***	-0.058***
	(0.03)	(0.03)	(0.003)	(0.007)
× 4th price quartile	-0.37***	0.059	-0.048***	-0.064***
	(0.03)	(0.03)	(0.003)	(0.006)
N	6 408 472	6 268 551	6 172 096	6 045 454
R^2	0.29	0.83	0.14	0.40
Year × Prod × Dest FE	Y	Y	Y	Y
Firm × Prod × Dest FE	N	Y	N	Y

Notes: Standard errors clustered at the firm-destination-product level between parentheses. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

prices, as the market share of low-cost countries increases. This finding is consistent with a response by French firms to low-cost competition, aiming at escaping the increasing competitive pressure at the bottom of the price distribution. This price response might be due to a change in the markup charged by these firms or by an increase in their product quality, raising their marginal costs. The model presented in the next section will allow for the possibility that foreign competition impacts the quality and markup decisions of firms, which results in price adjustments. Moreover, we will be able to use the structure of the model to disentangle the contribution of each margin, markup and quality, in the observed increase in prices.

Overall, the stylized facts presented in this section suggest that varieties that are closer in the product space, and in particular in the price distribution, display stronger substitution patterns. Standard models of demand, in which all varieties are equally substitutable within a product category, cannot account for the observed heterogeneity in the effects of foreign competition. In the next section, we develop an empirical model that can not only account for these patterns, but also generate realistic implications for the markup distribution, and for the endogenous quality response of firms to competition changes.

3 Model

In this section, we present an empirical model of trade with realistic substitution patterns between varieties and endogenous product quality. Specifically, we follow Brenkers and Verboven (2006) by developing a random coefficients nested logit model (RCNL) that combines hetero-

Table 3: Price responses to low-cost competition

Dependent variable:	*log price* (1)	(2)
2nd price quartile	0.66***	.
	(0.002)	
3rd price quartile	1.05***	.
	(0.002)	
4th price quartile	1.74***	.
	(0.002)	
Low-cost penetration		
× 2nd price quartile	-0.32***	-0.60***
	(0.008)	(0.01)
× 3rd price quartile	-0.33***	-0.92***
	(0.008)	(0.01)
× 4th price quartile	-0.58***	-1.56***
	(0.010)	(0.01)
N	6 408 472	6 268 551
R^2	0.90	0.94
Year × Prod × Dest FE	Y	Y
Firm × Prod × Dest FE	N	Y

Notes: Standard errors clustered at the firm-destination-product level between parentheses. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

geneity in consumer preferences with a nested structure in the error term of the model. This specification is particularly relevant for international trade data in which a variety is characterized by its product group. The RCNL model allows us to estimate specific substitution patterns between varieties belonging to the same product group but will also capture realistic competition effects along the quality ladder. In addition to capturing complex substitution patterns, the presence of heterogeneous consumers generates further desirable features such as variable markups correlated with product quality, and quality adjustments in response to a changing competitive environment.

We first describe the role of heterogeneous consumers by deriving the demand function of a product variety. 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 producers.

3.1 Demand Side

Preferences The global economy is a collection of markets m, each populated with a continuum of heterogeneous consumers. In the empirical application, a market will be a destination country×year pair. However, for the clarity of the exposition, we will ignore the market subscript m whenever possible. For a given industry (i.e. footwear), consumers can choose among $J+1$ varieties (J foreign varieties plus one outside good, corresponding to the domestic variety).

The utility derived by consumer i from consuming variety j is

$$u_{ij} = q_{ij}^{\exp(\alpha_i)} \exp\left(\delta_j + \bar{\epsilon}_{ij}\right) \quad j = 0, \cdots, J. \tag{2}$$

This formulation of the utility function reveals that the consumer cares about the quantity q_{ij} she consumes, as well as about her personal valuation of the product $\exp\left(\delta_j + \bar{\epsilon}_{ij}\right)$. This valuation is composed of a common element δ_j that raises the valuation of variety j for all consumers, and a utility shock $\bar{\epsilon}_{ij}$ that is consumer-specific. Therefore, consumers disagree on the valuation of varieties despite the existence of characteristics that raises the valuation of a variety for all consumers. In this utility function, α_i drives the relative importance of quality and quantity in consumer i's preferences and will quantify the price elasticity of each consumer. 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.

In the empirical application, we decompose the common valuation δ_j between observed and unobserved characteristics and two types of fixed effects. Specifically, we write δ_j as follows:

$$\delta_j = \beta x_j + \gamma_{g(j)} + \underbrace{\gamma_{f(j)} + \xi_j}_{\text{Quality } \lambda_j}, \tag{3}$$

in which x_j are observed characteristics of variety j and $\gamma_{g(j)}$ is a fixed effect for the product segment g of variety j. When focusing on the footwear industry in the empirical section, a segment will be defined as a 6-digit product category. Finally, $\gamma_{f(j)}$ is a producer fixed effect associated with the firm or country producing variety j and ξ_j is a utility shifter that captures unobserved characteristics left to explain the common valuation of variety j. In this paper, we define the product quality λ_j as the sum of the firm fixed effect and unobserved characteristics ξ_j. As a result, it is interpreted as the common valuation of a variety after controlling for its product category and observed characteristics.

In order to capture different degrees of substitution within and across product groups, we introduce a two-level nested logit structure. This is particularly important in our application in which varieties are mostly characterized by the product category to which they belong. Specifically, we assume that the utility shock can be decomposed in three random shocks as follows

$$\bar{\epsilon}_{ij} = \zeta^1_{ig(j)} + (1-\rho_1)\zeta^2_{io(j)} + (1-\rho_1)(1-\rho_2)\epsilon_{ij}. \tag{4}$$

This formulation follows the nested logit literature and Brenkers and Verboven (2006) which introduces the RCNL. First, utility shock ζ^1_{ig} is common to all varieties within a same segment g of the industry.[17] Second, utility shock ζ^2_{io} is common to all varieties imported from a same origin country. Finally, shock ϵ_{ij} is "truly" idiosyncratic in the sense that it varies across varieties within segment-origin nests. The presence of random shocks ζ^1_{ig} and ζ^2_{io} implies that varieties can be more similar, and therefore more substitutable, within origin/segment nests than between. The strength of these substitution patterns within nests depends on parameters ρ_1 and ρ_2. These

[17] For instance, 6-digit product categories 640419 (Footwear – other than sportswear – with outer soles of rubber or plastics and uppers of textile materials) and 640192 (Footwear; waterproof, covering the ankle, rubber or plastic outer soles and uppers) correspond to two different segments of the footwear industry.

parameters govern the contribution of ζ^1_{ig} and ζ^2_{io} to the overall variance of utility shock $\bar{\epsilon}_{ij}$.

Consumers choice Each consumer i picks one variety j and consumes $q_{ij} = \frac{e(y_i)}{p_j}$ physical units, with $e(y)$ the total budget allocated by a consumer with income y to the sector (e.g. $e(y_i)$ is the budget that i spends on shoes in our empirical application), and p_j the unit price of variety j.[18] Therefore, the indirect utility associated to any variety j is

$$V_{ij} = \delta_j - \exp(\alpha_i) \ln p_j + \bar{\epsilon}_{ij}. \tag{5}$$

Consumers pick the variety that maximizes their indirect utility. Since indirect utilities are only defined up to a constant, we normalize the appeal of the outside good to zero: $\delta_0 + \bar{\epsilon}_{i0} = 0$. Consequently, the measured utility shifter δ_j of a foreign variety should be interpreted in deviation to the quality of the domestic variety, which we define as the outside good.[19] Under this normalization, it comes handy to write indirect utility of j in deviation to the utility of the outside good:

$$V_{ij} - V_{i0} = \delta_j + \mu_{ij} + \bar{\epsilon}_{ij},$$

with δ_j and μ_{ij} respectively the common and consumer-specific part of the indirect utility, defined as

$$\mu_{ij} \equiv -\exp(\alpha_i)\left(\ln p_j - \ln p_0\right).$$

Under standard distributional assumption on ϵ_{ij}, ζ^1_{ig} and ζ^2_{io}, we get a standard 2-level nested logit expression for the probability the i picks variety j:[20]

$$\mathbb{P}_{ij} = \mathbb{P}_i^{j|og} \times \mathbb{P}_i^{o|g} \times \mathbb{P}_i^{g} = \frac{\exp\left(\frac{\delta_j + \mu_{ij}}{1-\rho_1}\right)}{\exp\left(\frac{I_{iog}}{1-\rho_1}\right)} \times \frac{\exp\left(\frac{I_{iog}}{1-\rho_2}\right)}{\exp\left(\frac{I_{ig}}{1-\rho_2}\right)} \times \frac{\exp(I_{ig})}{\exp(I_i)} \tag{6}$$

in which $\mathbb{P}_i^{j|og}$ is the probability that consumer i picks variety j within segment-origin nest og; $\mathbb{P}_i^{o|g}$ the probability that i chooses origin o within segment g; $\mathbb{P}_i^{g}$ the probability that i prefers segment g. Moreover, these nested probabilities depend on the inclusive values defined as

$$\begin{cases} I_{iog} &= (1-\rho_1)\log \sum_{k\in\mathcal{J}_{og}} \exp\left(\frac{\delta_k + \mu_{ik}}{1-\rho_1}\right) \\ I_{ig} &= (1-\rho_2)\log \sum_{o\in\mathcal{O}_g} \exp\left(\frac{I_{iog}}{1-\rho_2}\right) \\ I_i &= \log\left(1 + \sum_{g\in\mathcal{G}} \exp\left(I_{ig}\right)\right) \end{cases}.$$

[18] 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.

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

[20] Specifically, we assume that (i) ϵ_{ij} follows a type-1 extreme value distribution, that (ii) the distribution of ζ^1_{ig} and ζ^2_{io} are such that $\zeta^2_{io} + (1-\rho_2)\epsilon_{ij}$ and $\bar{\epsilon}_{ij}$ are also distributed type-1 extreme value.

From individual to variety-level demand Having described individual purchasing decisions, we can now obtain the aggregate demand received by varieties in each market by integrating individual decisions over the distribution of consumers. The total revenue of a variety j is

$$r_j = \int e(y_i)\mathbb{P}_{ij}\, di \tag{7}$$

where $e(y_i)$ is the total expenditures of consumer i and $\mathbb{P}_{ij}$ its probability of choosing variety j. In order to perform this integration, we make two assumptions regarding the expenditures of consumers, and the distribution of consumer preferences. First, we assume that the expenditure of consumer i is proportional to its income y_i, which implicitly amounts to assuming that consumers have Cobb-Douglas preferences across sectors. Second, we assume that the distribution of α_i in the population is a linear function of two shocks: log-income $\ln y_i$ and an idiosyncratic shock ν_i such that

$$\alpha_i = \alpha + \pi \ln y_i + \sigma\nu_i\ , \qquad y_i\ \sim\ F(y),\, \nu_i\ \sim\ G(\nu). \tag{8}$$

We assume that both $\ln y_i$ and ν_i have a normal distribution. However, while the distribution of ν_i is standard, we allow for the mean and standard deviation of $\ln y_i$ to vary across markets. Therefore, the moments of the distribution $F()$ will vary across destination markets. In the empirical application, we calibrate these moments based on the income distribution observed in each destination market. For each country, we translate information on the GDP per capita and Gini indices to first and second moments of a log-normal distribution.[21] This specification allows the model to explain deviations in price elasticities across destinations, through the income distribution, but also within destination by allowing consumers to have different preferences for other reasons than their income level. The estimated model will capture these two sources of heterogeneity through the parameters π and σ.

From this distributional assumption, we can now redefine $\mathbb{P}_{ij}$ as $\mathbb{P}_j(y,\nu)$ so that the revenue of variety j can be written

$$r_j = \int y\,\mathbb{P}_j(y,\nu)\,F(y)\,G(\nu)\,dy\,d\nu. \tag{9}$$

Finally, we can derive the market share of variety j in the market, which will be used to estimate the parameter of the models. The expression of the market share s_j is

$$s_j \equiv \frac{r_j}{\sum_{j'\in\mathcal{J}} r_{j'}} = \int \mathbb{P}_j(y,\nu)\,\omega(y,\nu)\,dy\,d\nu\,, \tag{10}$$

with $\omega(y,\nu) \equiv \frac{y\,F(y)\,G(\nu)}{\int y\,F(y)\,G(\nu)\,dy\,d\nu}$ the share of consumers with characteristics (y,ν) in the total revenue of the sector. The revenue market share of variety j is the probability that a consumer picks the variety, averaged across consumers, and weighted by the budget of each consumer.

[21]See appendix B for details.

3.2 Supply Side

Having described demand fundamentals, we 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 regarding 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

$$\ln c_j = \eta_j \lambda_j + h\lambda_j^2 + \rho x_j + \gamma_{g(j)} + \gamma_{f(j)} + \varphi_j. \tag{11}$$

First, we assume that marginal cost vary with the same observed characteristics that are included in the demand shifter: the characteristics x_j as well as product category and firm fixed effects $\gamma_{g(j)}$ and $\gamma_{f(j)}$. More importantly, 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 features are worth highlighting 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 in 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 is crucial to ensure that firms choose a finite level of quality at the equilibrium.[22] Moreover, this degree of convexity disciplines 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 an adverse competition shock.[23]

3.3 Producer's Problem

In each market, firms simultaneity choose the price p_j and quality λ_j of the set of varieties they supply in this market. The total profit of a firm f in the market is

$$\Pi_f(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{j \in \mathcal{J}_f} \pi_j(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{j \in \mathcal{J}_f} r_j(\boldsymbol{\lambda}, \boldsymbol{p}) \left(1 - \frac{c_j(\lambda_j)}{p_j}\right), \tag{12}$$

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

[23]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.

with $\mathcal{J}_f$ the set of varieties supplied by producer f. When choosing their prices and quality, producers take into account cannibalization across varieties of their basket $\mathcal{J}_f$. For clarity of exposition, the rest of this section presents analytical results corresponding to the special case of a single-variety producers. The exposition of the model with multi-product firms, which is used in the estimation procedure, is relegated to appendix A.

Optimal pricing The optimal pricing rule of a firm producing a single-variety j is:

$$p_j^* = \left(1 - \frac{1}{\frac{\partial \ln r_j}{\partial \ln p_j}}\right) c_j = \left(1 + \frac{1}{\int \exp(\alpha_i)\, \mathcal{E}_j(y,\nu)\, \omega_j^{(2)}(y,\nu)\, dy\, d\nu}\right) c_j\,, \tag{13}$$

with $\omega_j^{(2)}(y,\nu) \equiv \frac{\mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)}{\int \mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu}$ the share of consumer i in the revenue of variety j and $\mathcal{E}_j(y,\nu)$ the semi-elasticity of the purchasing probability $\mathbb{P}_j$ with respect to the utility shifter δ_j:[24]

$$\begin{aligned}\mathcal{E}_j(y,\nu) \equiv \frac{\partial \ln \mathbb{P}_j(y,\nu)}{\partial \delta_j} =& \frac{1}{1-\rho_1}\left(1 - \mathbb{P}^{j|og}(y,\nu)\right) + \frac{1}{1-\rho_2}\left(1 - \mathbb{P}^{o|g}(y,\nu)\right) \mathbb{P}^{j|og}(y,\nu) \\ &+ \left(1 - \mathbb{P}^{g}\right) \mathbb{P}^{j|og}(y,\nu)\, \mathbb{P}^{o|g}(y,\nu).\end{aligned}$$

Intuitively, the markup charged by a producer is an inverse function of the price elasticity of the average consumer it serves. This result highlights a desirable feature of a model with random coefficients: markups charged by a producer are increasing with the quality of its products. This is because higher quality λ_j decreases the weight $\omega_j^{(2)}$ of price-elastic consumers in the sales of variety j. By contrast, in models with a representative consumer, quality bears no direct impact on markups. More specifically, when consumers are symmetric, product quality only impacts mark-ups through market shares. One can see that by deriving the optimal mark-up in absence of heterogeneity across consumers:

$$\frac{p_j}{c_j} = 1 + \frac{1}{\exp(\alpha)\mathcal{E}_j} = 1 + \frac{1}{\exp(\alpha)\left[\frac{1}{1-\rho_1}\left(1 - \mathbb{P}^{j|og}\right) + \frac{1}{1-\rho_2}\left(1 - \mathbb{P}^{o|g}\right) \mathbb{P}^{j|og} + \left(1 - \mathbb{P}^{g}\right) \mathbb{P}^{j|og}\, \mathbb{P}^{o|g}\right]}.$$

In this special case, the markup of a variety j from segment g shipped from origin o will only depend on the price elasticity of the representative consumer $\exp(\alpha)$ and the market shares associated with the variety and the nests to which it belongs. In other words, without heterogeneity in consumers preferences, quality bears no impact on markups *after controlling for market shares*. Therefore, while most trade models can only explain the correlation between prices and quality by the higher cost of quality, our framework can also explain an impact of quality on prices through markup variations.

Optimal quality Similarly to prices, producers choose the quality of their products to maximize their profits. Producers operate a trade-off between supplying an appealing product or an affordable product: higher quality leads to an increase in the sales of a firm, conditional on prices, but also raises the marginal cost of production. Therefore, the optimal quality chosen

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

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. Formally, the optimal quality of a single-variety producer verifies

$$\lambda_j^* = \frac{1}{2h}\left(\tilde{\alpha}_j^{-1} - \eta_j\right) \qquad \text{with} \qquad \tilde{\alpha}_j \equiv \int \exp(\alpha_i)\,\omega_j^{(3)}(y,\nu)\,dy\,d\nu, \tag{14}$$
$$\omega_j^{(3)}(y,\nu) \equiv \frac{y\,\mathcal{E}_j(y,\nu)\,\mathbb{P}_j(y,\nu)\,F(y)\,G(\nu)}{\int y\,\mathcal{E}_j(y,\nu)\,\mathbb{P}_j(y,\nu)\,F(y)\,G(\nu)\,dy\,d\nu}.$$

$\tilde{\alpha}_j$ is a weighted average price elasticity of variety j's residual consumers. Introducing this variable in equation (14) helps us summarize the determinants of firm product quality. First, the optimal quality set by a producer depends on the elasticity of its costs to quality: producers with a small η_j are able to supply 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 producer serves, through variable $\tilde{\alpha}_j$. When a producer serves consumers with a low price-elasticity, it 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 producers invest in quality.

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 (14) 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 detail the data construction.

4.1 Data Preparation

The footwear industry We estimate the model using data from the footwear industry. Specifically, we focus on the HS6 product categories belonging to the HS2 category 64: 'Footwear; Gaiters and the like; parts of such articles', excluding product categories associated with shoe parts.[25] We implement our estimation strategy using the footwear industry for two reasons. First, shoes are a well-defined consumer good which allows us to obtain prices that are consistent and can be compared across varieties. Second the footwear industry is relevant because it mimics the recent trend in manufacturing. The Chinese market share in the footwear industry has increased significantly throughout the period, moving from 20% in the average destination market in 1997 to 30% in 2010. In light of these features, we expect the footwear industry to exhibit a 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 by almost 40% during the sample period, the market share of low-price French shoes collapsed by more than 60% on average. In the meantime, high-price French shoes also lose market shares, but at a much slower rate.[26]

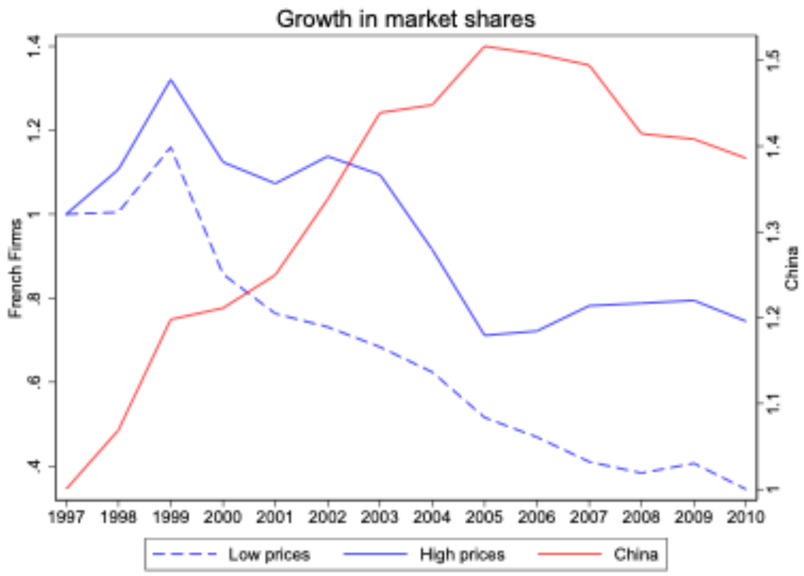

FIGURE 1: Chinese competition Hits Cheap Shoes Harder

Notes: The figure shows the evolution of the average market share for three groups of export flows: Chinese footwear, high-price French footwear and low-price French footwear. On each HS6-destination market, a French variety is considered high-price (respectively low-price) if it belongs to the fourth (respectively first) quartile of the pre-2001 local price distribution. Once French varieties are grouped into price categories, we compute the aggregate market share of high and low price varieties by HS6-destination-year and average them across HS6-destination markets, weighting each market by the number of varieties.

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

[25] We exclude HS6 groups starting with 6406, designed for various types of shoe parts.

[26] To construct this figure, we divide French varieties in quartiles based on their prices before 2001. We then compute the market share of each quartile in each destination market, and average these market shares across destinations.

report for each year from 1997 to 2010, the distribution of French and Chinese prices, weighted by their respective market shares. This figure shows that, as the market share of China increases, the price distribution of French shoes diverges upward from Chinese 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 for French shoes. Both of these mechanisms suggest a heterogeneous impact of low-cost competition along the price dimension.

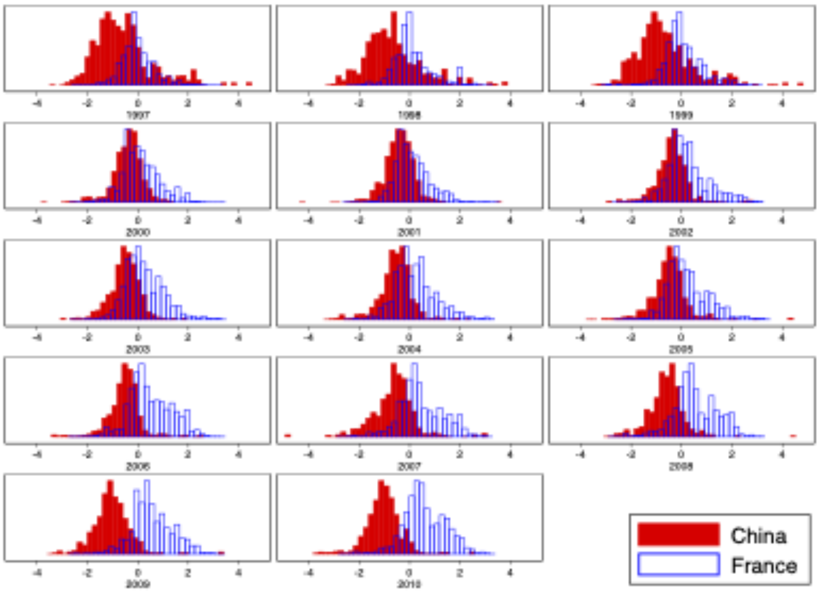

FIGURE 2: The price of French shoes diverge from Chinese competition

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

Estimation sample The estimation procedure requires the market shares and prices of all varieties within a specific market. In our context, we define a market as a destination country - year pair,[27] and a variety as the combination of a six-digit product category and a producer. Because we combine firm-level data from France and product-level data from other countries, a producer can be a French firm or a foreign country.[28] Moreover, the estimation procedure requires to construct prices that consumers face in each destination market. Therefore, we convert FOB 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 for the 2-digit category 'Leather, Leather and Footwear' 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. As a result, we obtain import prices which reflect the final

[27] 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 8 in appendix B for details.

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

price observed by consumers in the destination market. Before taking the model to the data, we perform a number of operations to avoid the presence of anomalous observations in the estimation sample. We follow the same procedure used in section 2, only this time on the subsample of footwear exports: we eliminate markets with a small number of producers, drop observations from French firms that display extreme variations, and correct extreme prices from other countries' exports.[29] This cleaning procedure leaves us with 319 607 observations, including 145 420 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 4, we report summary statistics for the 3 316 distinct French firms that are part of the sample.[30] Notice that the median firm has only nine observations. This sparsity is typical of trade data. Moreover, we see a large dispersion in the price of one kilogram of shoes, ranging from 7 Euros at the 5th percentile to 231 Euros at the 95th percentile. Finally, the market shares of French firms are small in foreign markets. The average French variety has a market share of 0.004 percent in a destination-year market and 0.16 percent when measured within a specific HS6 product category.

Table 4: Summary statistics for French firms

	Mean	*p5*	*p25*	*p50*	*p75*	*p95*
By firm:						
# observations	43.9	2	3	9	33	191
# destinations	5.8	1	2	3	8	20
# products	3.1	1	1	2	4	10
Price	63.5	6.6	15.9	31.4	67.3	231.3
Market share (%)	0.004	$2.58e^{-6}$	0.00004	.00024	.0015	.018
Nested Market share (%)	0.16	0.00004	0.0007	.0053	.036	.52

Notes: FOB Prices per kilogram in Euros. Sample of 3316 firms.

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.[31] 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 for broad product classifications. As a consequence, we compute the market share of the outside good as the domestic market share for the 2-digit category 'Leather, Leather and Footwear'. In order to estimate the price of this outside good, 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:

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

[29] These different steps are described in B.

[30] 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.

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

and we construct the domestic prices from the first fixed effects $\hat{\gamma}^{(1)}_{ct}$ to obtain the price of the outside good at the country-year level. This methods allow us to measure the average price of the shoes exported by this country, accounting for differences in product portfolio and destination markets.

4.2 Demand Side Estimation

We start by presenting the estimation procedure, that closely follows the Generalized Method of Moments (GMM) method developed in Berry et al. (1995). 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 The parameters of our demand system is made of five parameters, $\boldsymbol{\theta} \equiv \{\alpha, \pi, \sigma, \rho_1, \rho_2\}$ and is estimated using a non-linear GMM estimator. GMM algorithms rely on orthogonality conditions between a structural error term $\xi(\boldsymbol{\theta})$, function of the model parameters, and a set of instruments $Z = [z_1, ..., z_L]$ such that

$$E\left[z_l\, \xi(\boldsymbol{\theta}_0)\right] = 0, \qquad \text{for} \quad l = 1, .., L \tag{15}$$

where $\boldsymbol{\theta}_0$ is the true value of the parameter.

We now describe the strategy to recover the structural error ξ_{jdt}, as a function of $\boldsymbol{\theta}$ 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 (10), the market share of a variety j in destination d at date t is

$$s_{jdt}(\boldsymbol{\delta}_{dt}, \boldsymbol{p}_{dt}; \boldsymbol{\theta}) = \int \mathbb{P}_{jdt}(y, \nu, \boldsymbol{\delta}_{dt}, \boldsymbol{p}_{dt}; \boldsymbol{\theta})\, \omega_{dt}(y, \nu)\, dy\, d\nu\,, \tag{16}$$

For each market dt, this formulation provides a mapping between the vector of common utility shifters $\boldsymbol{\delta}$ and the vector of predicted market shares $\boldsymbol{s}(\boldsymbol{\delta}, \boldsymbol{p}; \boldsymbol{\theta})$. Therefore, conditional on the set of parameters $\boldsymbol{\theta}$ and a vector of observables prices $\boldsymbol{p}$, we can solve for the unknown vector $\boldsymbol{\delta}$ such that the vector of predicted market shares $\boldsymbol{s}(\boldsymbol{\delta}, \boldsymbol{p}; \boldsymbol{\theta})$ equals the vector of observed market shares $\boldsymbol{S}$. For this purpose, we use the contraction mapping suggested by BLP: from a given vector $\boldsymbol{\delta}^{(h)}$ at iteration h, we compute $\boldsymbol{s}(\boldsymbol{\delta}^{(h)}, \boldsymbol{p}; \boldsymbol{\theta})$ and iterate using

$$\boldsymbol{\delta}^{(h+1)} = \boldsymbol{\delta}^{(h)} + (1 - \max(\rho_1, \rho_2)) \cdot \left[\log \boldsymbol{S} - \log \boldsymbol{s}(\boldsymbol{\delta}^{(h)}, \boldsymbol{p}; \boldsymbol{\theta})\right]. \tag{17}$$

until the minimum of the vector of squared difference between $\boldsymbol{\delta}^{(h+1)}$ and $\boldsymbol{\delta}^{(h)}$ is less than 10^{-12}.[32] Note that this contraction mapping differs from the original BLP formulation. In the presence of nests, Grigolon and Verboven (2014) shows that the contraction must be augmented with the term $(1 - \max(\rho_1, \rho_2))$.

We denote the resulting vector of common utility terms $\boldsymbol{\delta}(\boldsymbol{S}, \boldsymbol{p}; \boldsymbol{\theta})$ and regress this vector on

[32] The convergence of the contraction mapping is accelerated using the Squarem acceleration method developed in Varadhan and Roland (2004), and written in Matlab by Conlon and Gortmaker (2019). Moreover, we use 100 draws from Halton sequences to numerically approximate the integrals in the computation of $\boldsymbol{s}(\boldsymbol{\delta}^{(h)}, \boldsymbol{p}; \boldsymbol{\theta})$.

the components of the common utility terms:

$$\delta_{jdt}(\boldsymbol{S}, \boldsymbol{p}; \boldsymbol{\theta}) = \beta x_{jdt} + \gamma_{g(j)} + \gamma_{f(j)} + \xi_{jdt}, \tag{18}$$

with $\gamma_{g(j)}$ and $\gamma_{f(j)}$ product and producer fixed effects respectively, and x_{jdt} a set of dummies to identify entering and exiting firms.[33] From this regression, we obtain measures of quality, defined as $\hat{\lambda}_{jdt} \equiv \hat{\gamma}_{f(j)} + \hat{\xi}_{jdt}$, and the structural errors $\hat{\xi}(\theta)$ that allow us to compute the orthogonality conditions identifying the vector of parameters $\boldsymbol{\theta}$. 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 nesting structure and the distribution of the random coefficient. The other parameters (i.e. those entering the mean utility level) can be directly obtained by linear regression, hence reducing the dimensionality of the search algorithm.[34]

We obtain our GMM estimates $\hat{\boldsymbol{\theta}}$ 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

$$\hat{\boldsymbol{\theta}} = \text{argmin}_{\theta} \quad \hat{\xi}(\theta)' Z \Phi Z' \hat{\xi}(\theta) \tag{19}$$

where Φ is the weighting matrix $\Phi = (Z'Z)^{-1}$. Moreover, we obtain standard errors for our estimator using the GMM standard errors from Newey and McFadden (1994):

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

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

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

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 $\hat{\lambda}_{jdt} \equiv \hat{\gamma}_{f(j)} + \hat{\xi}_{jdt}$ for each variety j in destination d, identified from the unobserved characteristics of a variety that increase its valuation for all consumers. 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 compute the variety-specific markup using a version

[33] We introduce these controls to account for partial-years effects: when firms enter a market, their sales are likely to be small because they do not export for a full year. We control for this possibility to avoid contaminating our quality estimates. See Bernard et al. (2017) and Piveteau (2020) for papers treating this bias.

[34] 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 fixed effects.

of equation (13) that accounts for the presence of multi-product firms.[35] 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 separately estimate the parameters entering the marginal cost function.

Instruments The estimation of the model requires three types of instruments to respectively identify the price-elasticity of demand, the nested structure of the demand system and the distribution of random coefficients across consumers.

The first set of instruments for prices needs 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 import tariffs between countries. Tariffs directly affect the final price charged by a firm in foreign markets. Moreover, since 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.[36] Specifically, we use tariffs data from TRAINS and the Market Access Map (MAcMap) dataset that provides bilateral measures of applied tariff duties.[37] In order to allow for heterogenous responses between firm-level trade and aggregate trade from foreign countries, we interact this tariff measure with a dummy for French exporters. This echoes the adjustment for foreign varieties that we describe in the next section.

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.[38] 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

[35] See equation (23) in appendix A.
[36] See Fontagné et al. (2018) for a similar use of tariffs.
[37] Appendix B provides details on the dataset.
[38] See Piveteau and Smagghue (2019) for further discussion on this firm-level instrument.

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 cost shifters, we also need two instruments to identify the parameters ρ_1 and ρ_2 that measure the patterns of substitutions within and between nests. To estimate these parameters, we follow the literature and include the number of competitors in the market, as well as the number of firms in the product category and product category $\times$ origin nests.[39] Finally, we also derive instruments that identify the distribution of the random-coefficients in our demand system. First, we follow Gandhi and Houde (2017) to construct "Differentiation IVs": 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. Moreover, we interact the cost shifters presented in the previous paragraph with the average gdp per capita of the destination. This aims at identifying variations in price-elasticity with the income of the consumer.

In total, our baseline specification contains three cost shifters (tariffs to destination, tariffs interacted with a French dummy and import-weighted exchange rates), three nested instruments (number of firms in the market, in the nest and in the sub-nest) and four differentiation IV (three cost shifters interacted with the income in the destination and number of firms in the market within one standard deviation of prices). This total of ten instruments identifies the five structural parameters of our model.

Product-level data and hidden varieties The estimation of the demand system combines micro-level data of French exporters but also product-level data from the many foreign countries. The use of trade flows at an aggregate level – HS6 $\times$ origin – rather than firm level can be an issue for two reasons. First, we ignore the dispersion in firm's quality and prices that exists at the microeconomic level. This heterogeneity might have consequences for 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 implies 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 aggregate data. Using this new simulated dataset, we rerun our counterfactual experiments. Details and results of this procedure are displayed in appendix C. We find that this dispersion has little impact on the results of our counterfactual experiments. Even though this procedure is an imperfect test, it is reassuring that the measurement issues

[39] See Goldberg and Verboven (2001) for an example in the estimation of a nested logit model.

created by the use of aggregate data do not have a strong impact on our results.

The second issue for the estimation is that the interpretation of the demand shifter as a measure of quality is not valid for foreign countries. When using aggregate data, this demand shifter can be decomposed into the number of exporting firms and the average product quality of these firms. This presence of hidden varieties is an issue for identification: while the average product quality can be seen as exogenous to tariffs changes, this is certainly not the case for the number of exporters. In other words, the price elasticity identified for foreign varieties will conflate the intensive margin, the change in exports for each firm in response to a price change, with the extensive margin, the increase in the number of exporters in response to lower prices. In order to make sure that we estimate the firm-level price elasticity, we implement two alternative strategies. First, we allow the price of an exported variety to have a differentiated impact for countries relative to firms. More precisely, we add an interaction between the price term and a dummy for foreign countries to capture differences in the average price elasticity between French firms and foreign countries. This additional term captures the effect of the extensive margin and ensures that the price-elasticity estimated for French firms is the firm-level elasticity. Alternatively, we estimate the model using French firms only. In this specification, we use data from foreign countries to construct market shares and instruments but estimate the model using moments from French observations only. As a result, we measure price elasticities and random coefficients on the set of French firms only, avoiding the bias from the adjustment in hidden varieties. Both of these approaches show consistent results: we find that foreign countries have a larger response to cost shifters and as a result, the correct price elasticity estimated on the sample of French firms is smaller.

Finally, the presence of aggregate data from foreign countries also imply that the variety-level outcomes of the estimation - product quality, markups and marginal costs - are not valid for foreign varieties. Therefore, we only use these measures to characterize the distribution of these outcomes for French firms.

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. The model derived in section 3 shows that the extent of this response depends on the convexity of the marginal cost function. Fortunately, the model also provides guidance on how to estimate the parameter dictating this convexity and therefore, quantifying the contribution of this quality response.

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 (14), we have:

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

with $\tilde{\alpha}_{jdt}$ a weighted average of the price elasticity, as defined in equation (14). 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 $\tilde{\alpha}^{-1}$.

In addition, we can derive a second linear regression that can identify the parameter h. Combining the marginal cost function (equation (11)) and the first order condition on quality leads to the following formulation of the marginal costs:

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

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 construct an exogenous version of $\tilde{\alpha}^{-1}$, denoted $\breve{\alpha}^{-1}$, that captures changes in the average price elasticity due to changes in competition and not due to changes in the firms' own characteristics.

To explain how we construct $\breve{\alpha}_{jdt}^{-1}$, let us define $\boldsymbol{\delta}_{dt}^{-j}$ and $\boldsymbol{p}_{dt}^{-j}$ to be respectively the vector of utility shifters and prices of the competitors of variety j. $\breve{\alpha}_{jdt}^{-1}$ is obtained by fixing the own price and utility shifter of j to their initial values δ_{jd0} and p_{jd0} and computing the resulting individual purchasing probabilities:

$$\breve{\mathbb{P}}_{jdt}(y,\nu) = \mathbb{P}_{jdt}(y,\nu,\delta_{jd0},p_{jd0},\boldsymbol{\delta}_{dt}^{-j},\boldsymbol{p}_{dt}^{-j};\boldsymbol{\theta})$$

From there, we obtain $\breve{\alpha}_{jdt}^{-1}$ by computing the inverse weighted price-elasticity using purchasing probabilities $\breve{\mathbb{P}}_{jdt}(y,\nu)$ instead of $\mathbb{P}_{jdt}(y,\nu)$:

$$\breve{\alpha}_{jdt}^{-1} = \frac{1}{\int \exp(\alpha_i)\breve{\omega}_{jdt}(y,\nu)\,dy\,d\nu}$$
$$\text{with} \quad \breve{\omega}_{jdt}(y,\nu) = \frac{y\,\breve{\mathcal{E}}_{jdt}(y,\nu)\,\breve{\mathbb{P}}_{jdt}(y,\nu)\,F(y)\,G(\nu)}{\int y\,\breve{\mathcal{E}}_{jdt}(y,\nu)\,\breve{\mathbb{P}}_{jdt}(y,\nu)\,F(y)\,G(\nu)\,dy\,d\nu},$$

and $\breve{\mathcal{E}}_{jdt}(y,\nu)$ is similarly defined using the initial characteristics of variety j and the characteristics of its competitors.

Firms differ in their initial characteristics, yet the time variation of $\breve{\alpha}_{jdt}^{-1}$ is only due to changes in the characteristics of competitors – $\boldsymbol{\delta}_{dt}^{-j}$ and $\boldsymbol{p}_{dt}^{-j}$ – that shift the average residual consumer faced by each French firm. Therefore, this variable gives us exogenous variations in the average price elasticity, that triggers quality and marginal cost responses.

We use $\breve{\alpha}_{jdt}^{-1}$ to estimate the relationship between quality and average price elasticity, equation (14), and between marginal cost and the square of the average price elasticity, equation (20). Because the variation of $\breve{\alpha}_{jdt}^{-1}$ is only exogenous across time, we will use first differences and fixed effects to measure the response in quality and marginal costs to an exogenous change in $\breve{\alpha}_{jdt}^{-1}$. These regressions will deliver 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

We present the estimation results of the demand system in several steps. First, we estimate a simple logit model to show that our instrumentation for prices with cost shifters has the expected impact on the estimated price elasticity. Second, we show the results of the nested logit model, which can be estimated with two stage least squares (2SLS), to highlight the importance of the nested structure. Finally, we present the results of the RCNL estimation, introducing random coefficients across consumers.

The results of the estimation are presented in table 5. Columns (1) and (2) estimate a standard logit model: we regress the normalized logarithm of the market share $\log s_{fdpt} - \log s_{0dt}$, on the normalized logarithm of prices $\log p_{fdpt} - \log p_{0dt}$ and a set of controls: all specifications in this table include producer and hs6 fixed effects and dummies for entering and exiting varieties. These columns validate our instrumental strategy by showing that using cost shifters as instruments, unlike the OLS results, lead to a negative price elasticity. In column (3), we estimate the nested logit model by including as regressors the share of a variety in its HS6 category and in its product category $\times$ origin groups. Moreover, we include an interaction between prices and the income in the destination and allow for the price elasticity to be different for country-level data relative to firm-level data. This specification shows that there are important nesting patterns in preferences: both parameters ρ are significantly different from zero which indicates that consumers express more substitution between varieties within the same product category and coming from the same origin. Moreover, we see that richer countries have a lower price elasticity, which suggests that income is a source of heterogeneity in preferences.[40] Finally, we confirm that country-level trade flows have a larger price elasticity than firm-level flows: the coefficient of -1.28 indicates that an increase in export prices have a larger impact on country-level trade, which is consistent with a reduction in the number of hidden varieties in these trade flows. To confirm that these patterns of substitution are not entirely driven by country-level observations, column (4) shows the result of this logit model using French firms only. These results show that income still has an impact on price-elasticity, although smaller, and we find very similar estimates for parameters ρ which suggests that these nesting patterns across products also apply to firm-level varieties.

Finally, columns (5) and (6) show the results of the RCNL models, respectively using the full sample and a sample with French firms only. The results confirm the importance of the nests in consumers choices, despite the presence of random coefficients: we find estimates for the parameters ρ to be very close to the ones we found in the nested logit. The value of these

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

Table 5: Estimation results

	OLS	2SLS	Nested Logit		RCNL	
	(1)	(2)	(3)	(4)	(5)	(6)
log price	0.073	-1.49	-0.53	-0.79		
	(0.006)	(0.03)	(0.04)	(0.03)		
log price $\times$ *Country*			-1.28		-0.91	
			(0.05)		(0.4)	
log price $\times$ inc_d			0.86	0.27		
			(0.02)	(0.01)		
$\log s_{j\|g}$ (ρ_1)			0.38	0.32	0.24	0.30
			(0.008)	(0.01)	(0.1)	(0.03)
$\log s_{j\|og}$ (ρ_2)			0.89	0.75	0.78	0.72
			(0.007)	(0.007)	(0.05)	(0.02)
α					0.12	-0.10
					(0.6)	(0.5)
π					-0.34	-0.21
					(0.2)	(0.1)
σ					0.01	0.01
					(7.1)	(9.3)
Average price elast.	0.073	-1.49	-4.59	-3.05	-4.81	-3.60
Sample	Full	Full	Full	French	Full	French
N	319 607	319 607	319 607	145 420	319 607	145 420
First stage F-stat		4 562.9	1 133.7	571.5		

Notes: Standard errors between parentheses clustered at the producer level. All specifications include producer (firm or country) fixed effects, hs6 fixed effects and dummies for entering and exiting varieties. Instruments are the three cost shifters for specification (2), and the cost shifters, their interaction with the destination log average income and the number of firms in each level of nests (market, product group and product group-origin) for specifications (3) and (4) (total of 9 instruments). For specification (5) and (6), we augment the set of instruments with the number of competitors in the market located within one standard deviation in the price distribution (total of 10 instruments).

parameters is slightly smaller, probably due to the facts that random coefficients capture some of the substitution patterns in the data. Regarding the impact of prices, we find an estimate of α equal to 0.12: this leads to a price elasticity of $-\exp(0.12) = -1.13$ for an atomistic firm. However, the average price elasticity across French firms is 4.59, which reflects the fact that firms have significant market power within their nest. Moreover, we find that a consumer's income does reduce its price elasticity with a negative parameter π significantly different from zero: an estimate of -0.34 means that a consumer with an income twice larger than the average consumer has a price-elasticity of $-\exp(0.12 - 0.34) = -0.80$. Regarding the impact of other sources of heterogeneity, we do not find a significant role for other shocks, suggesting the the income distribution captures the essential of the dispersion in price elasticity across consumers. To validate that the identification of these coefficients does not rely solely on product-level trade flows from foreign countries, we estimate the RCNL model with only French firms in column

(6). We find very similar results regarding the importance of the nests, as well as the role of income in generating differences in preferences.

Having described these parameter estimates, we now describe several outcomes of the model which further illustrate the implications of heterogeneous preferences. Specification (5) is our preferred specification since it includes both the nested structure and random coefficients in preferences. Therefore, we use it as a baseline in the rest of the paper, both for our post-estimation analysis and our counterfactual 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 and adjust their markup to 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 (23), using parameter estimates from specification (5) in table 5 to parametrize the distribution of consumer preferences. The average markup among French varieties is around 30 percent, which is consistent with previous estimates found in the literature. Interestingly, we see a large variation in these markups: some products only have a 15 percent markup, while others are closer to 100 percent.

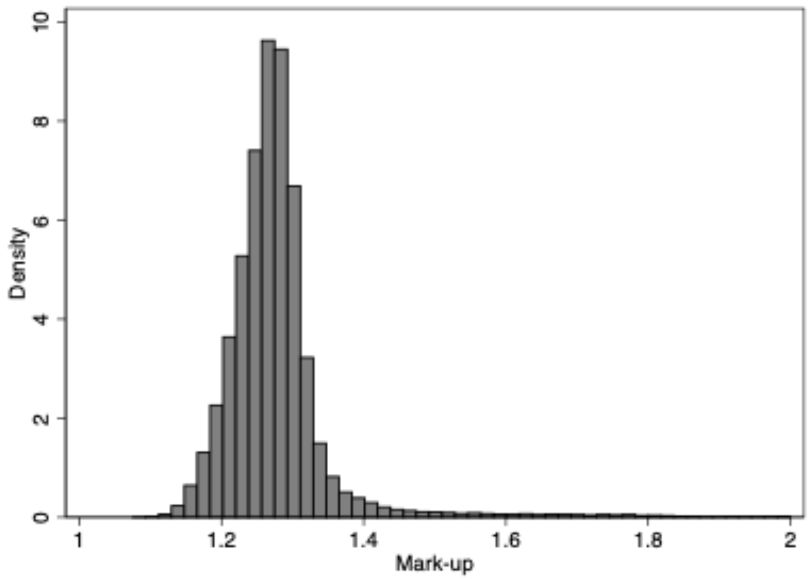

FIGURE 3: Distribution of markups of French firms

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 and marginal costs 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 the importance of these factors in driving the observed dispersion in markups, we report in figure 4 the relationship between markups and the market share of a variety within its product group $\times$ origin nest (left panel), and between markups and the logarithm of its marginal cost (right panel).[41] This figure shows that both factors matter in explaining the dispersion in markups. In terms of market power, an increase of 10 points in the nested market share increase the markup charged by a firm by 0.04. Similarly, firms with higher marginal costs, reflecting higher quality, also charge higher prices: a firm doubling its marginal costs will increase its markup by 0.02 on average. 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.

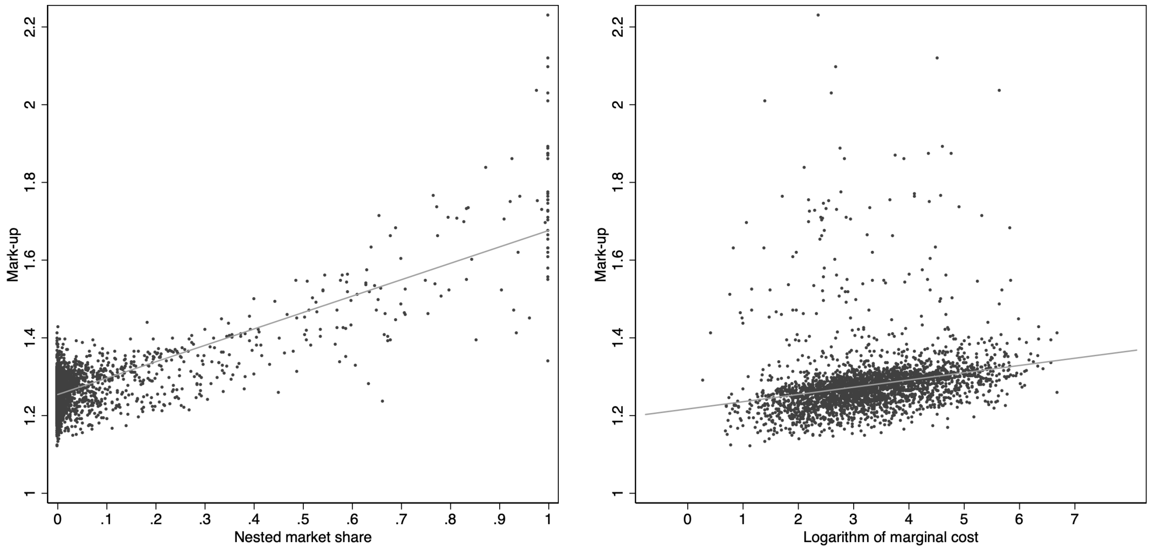

FIGURE 4: Correlation of markup with market share and quality

Notes: The figure is constructed using the sample of French firms only. Nested market share is the market share of a variety within its product category (HS6) $\times$ *origin nest. For clarity, the scatterplot only contains a two percent random sample of observations.*

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). From the left panel, 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

[41]We focus on the market share within nests because French firms have very small market shares in a destination market.

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 close to 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.

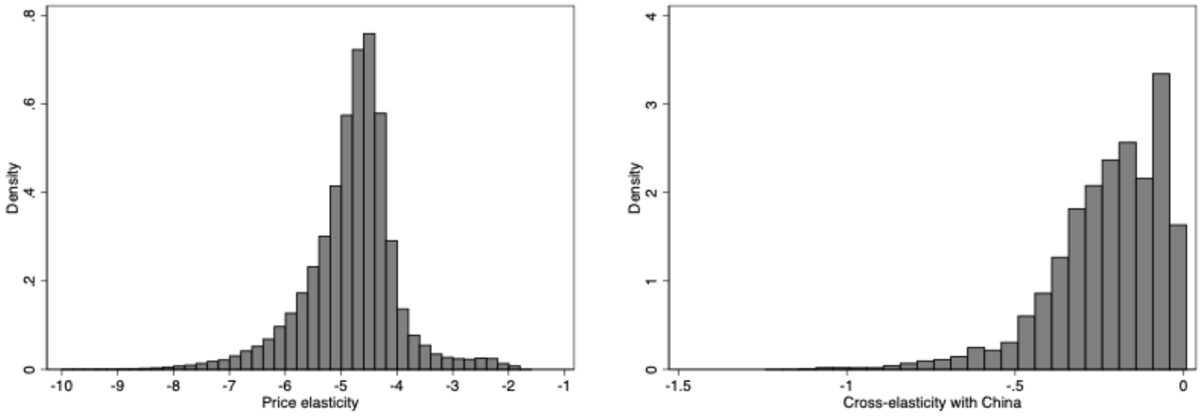

FIGURE 5: Distribution of own and cross-price elasticities (French firms).

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.[42]

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,

[42]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.

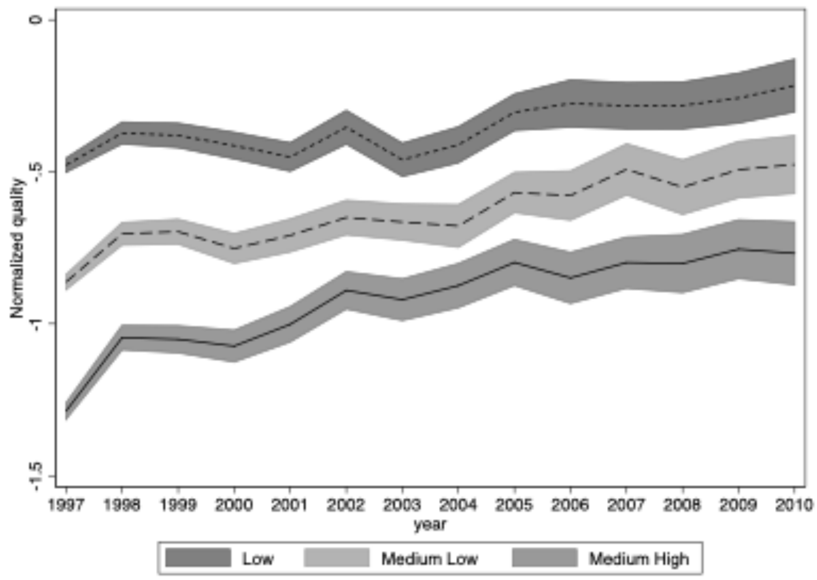

FIGURE 6: Low Price Varieties Upgrade their Quality over the Period

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.

we now present our estimates of the impact of quality upgrading on firm costs, that will discipline the quality response in our counterfactual experiment.

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. 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 change in competition. In section 4, we provide two equations to identify this parameter h. First, the first order condition on quality, equation (14), 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 6. In all specifications, we use two sets of fixed effects: firm×HS6×destination fixed effects so that we identify variations across times of our variables, hence looking at quality and marginal costs changes triggered by changes in competition, and HS6×destination×year fixed effects so that we identify the impact between firms exporting to the same destination.[43] In the first two columns, the relationship between quality and $\tilde{\alpha}^{-1}$ estimates the reduced form parameter $\frac{1}{2h}$, while columns 3 and 4 estimates the parameter $\frac{1}{4h}$.

[43] In table 10 in appendix D, we find very similar results using first differences and long differences instead of firm×HS6×destination fixed effects.

Table 6: Estimation results: supply side

	(1)	(2)	(3)	(4)	(5)
	quality λ_{jdt}		$\log mc_{jdt}$		*Stacked*
$\tilde{\alpha}^{-1}$	6.28 (0.06)				
$\breve{\alpha}^{-1}$		1.70 (0.3)			
$(\tilde{\alpha}^{-1})^2$			2.65 (0.01)		
$(\breve{\alpha}^{-1})^2$				1.20 (0.1)	
$\breve{\alpha}^{-1}$ or $\frac{(\breve{\alpha}^{-1})^2}{2}$					2.08 (0.2)
$\hat{h}$	0.08	**0.29**	0.09	**0.21**	**0.24**
N	123 526	123 526	123 526	123 526	247 052
R^2	0.96	0.91	0.99	0.88	1.00

Notes: Firm-level clustered standard errors between parentheses. All regressions include firm-HS6-destination and destination-HS6-year fixed effects.

In both specifications, we start by regressing quality or marginal costs on the actual value of $\tilde{\alpha}^{-1}$. Because this variable is spuriously correlated with quality and marginal costs, we obtain very large coefficients of 6.28 and 2.65, which corresponds to a value for h around 0.1. In order to obtain consistent estimates for h, we use the exogenous version of $\tilde{\alpha}^{-1}$, $\breve{\alpha}^{-1}$, which avoids this mutual causality between $\tilde{\alpha}^{-1}$ and quality or costs: because $\breve{\alpha}^{-1}$ only varies with competitors' characteristics, the correlation between this variable and quality or costs captures the causal impact of competition on firm's decisions.[44] With this exogenous variable, we obtain much smaller coefficients, respectively 1.70 and 1.20, which leads to a larger value for h. Since h measures the convexity of marginal costs, a smaller quality and marginal costs response is explained by more convexity in the cost function. In order to take advantage of both specifications, we also run a stacked regression in column (5) which scales both specifications to obtain a single estimate for h. With this specification, we obtain a value for h of 0.24. In table 10 in appendix D, we explore the robustness of this parameter estimate looking at first differences and longer differences to account for adjustment frictions in the short run. All these specifications lead to an estimate of h around 0.25, which is the estimate we use for our counterfactual experiment.

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

[44]Figure 11 in appendix D shows the scatterplots associated with these regressions.

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.[45] 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 Direct impact of Chinese competition on French firms

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 table 7 the impact of moving the characteristics of Chinese exports to their post 2007 levels on the market shares of Chinese products and French firms. For Chinese exporters, the median effect is a 260 percent increase of their market share which reflects the significant growth of Chinese exporters during these periods. However, we see a lot of dispersion across products and categories: more than 25 percent of these Chinese products lose market shares. This large number is explained by a reduction in the demand shifter for some products but is mostly explained by the increasing competition of other Chinese products. For instance, Chinese boots might lose market shares in Brazil because Chinese leather shoes gained so much in this destination market. Almost all French firms lose market shares as a result of this simulated China shock. The median French firm sees a 30 percent reduction in market shares and we see significant decreases in market shares for the vast majority of French firms.

TABLE 7: Effect of the simulated China shock

	p5	*p25*	*p50*	*p75*	*p95*	N
Chinese products	-0.87	-0.058	2.60	12.0	77.0	544
French firms	-0.90	-0.46	-0.30	-0.19	-0.022	6 729

Notes: Growth in market shares between the simulated and the actual 1997 equilibrium ($s_{97}^{sim}/s_{97}^{actual} - 1$)

[45] 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.

Having described the significant impact of this shock, we can now study how it has differently affected French firms along the price distribution. In each market, we divide the sample of French firms in 1997 based on their position in the local price distribution and compute the average change in market shares between the initial equilibrium and the simulated equilibrium with new characteristics for Chinese exporters. In order to control for the different level of competition across markets, we normalize the average loss in market share for a price decile relative to the top decile. As a result, we measure the additional loss in market share recorded by firms located in lower price deciles.

Figure 7 reports the heterogenous impact of Chinese competition across price deciles. In the left panel, we look at the heterogenous effects in a destination market for all French firms, regardless of the type of shoes they export. We find that firms located in the first price decile record an additional 20 percentage points decrease in market share relative to the top decile. This higher exposure of low-price firms can be explained by horizontal and vertical differentiation: horizontal differentiation because these firms could be exporting a type of shoes that Chinese firms produce more, and vertical because, conditional on the type of shoes, they produce low-quality products that resemble the varieties exported by Chinese firms. To disentangle these two effects, we also report in the left panel the effect that we obtain with a simple nested logit and no random coefficients.[46] In this model, we capture horizontal differentiation but rule out any role for vertical differentiation. We find that horizontal differentiation explains around two third of the heterogenous impact of competition, with the first decile having an additional 13 percentage points reduction in market shares on average.

To confirm the importance of vertical differentiation, the right panel of figure 7 looks at the impact of competition within destination×HS6 markets. Within these markets, French firms are affected by the increase of a single Chinese variety. As a result, the nested logit cannot predict any heterogeneous impact between price deciles, while the random coefficients nested logit can predict some heterogeneity through vertical differentiation. We find that being located in the first decile implies an additional 8 percentage points loss in market share relative to the top decile. Moreover, we can see a clear monotonic pattern across price deciles that shows that moving along the price distribution directly affects your exposure to Chinese competition.

In conclusion, these results imply that the rise of Chinese competition makes it 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 Quality and price responses to competition

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

[46] We set the parameters π and σ that govern the distribution of random coefficients to zero.

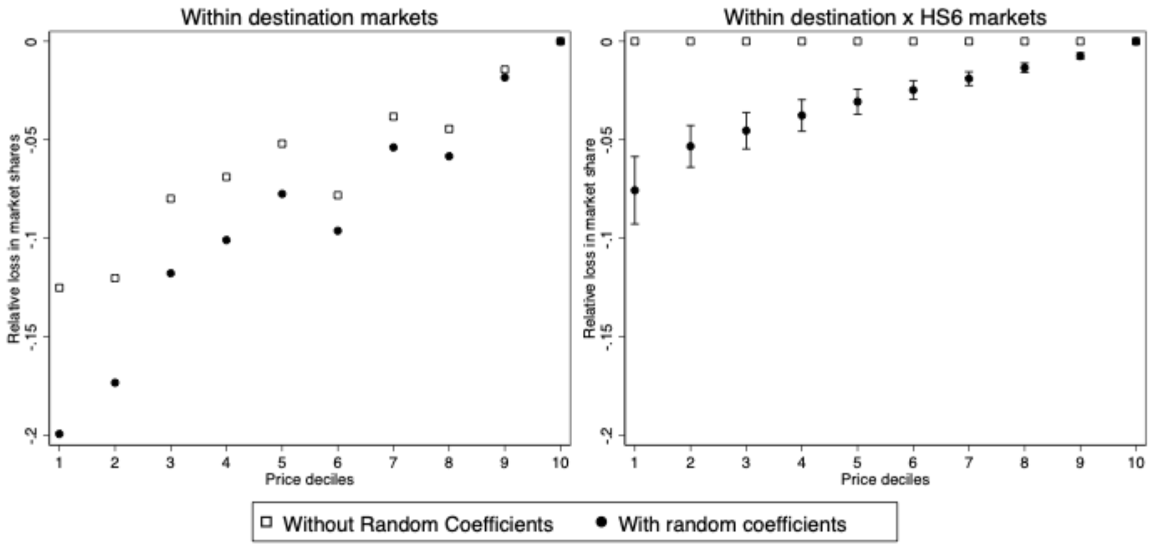

Figure 7: Effect of the China shock by price deciles (on French firms in 1997)

Notes: The figure reports the average log-change in market shares for all French firms in 1997, separately for each price decile and relative to the top 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. Price deciles are computed across French firms within a destination market in the left panel and within a destination-HS6 market in the right panel. The dark dots are computed using the full RCNL model while the white square are obtained by setting the random coefficients π and σ equal to zero (nested logit model).

fundamentals on French firms in 1997. Importantly, we only allow French firms to adjust their markup and quality levels, leaving unchanged the characteristics of other foreign exporters.[47]

The new equilibrium quality, markups and marginal costs are computed using the first-order conditions on quality, prices and the definition of the marginal costs. For exposition, we use the equations (14), (13) and (11) presented in section 3. However, we implement this algorithm with the multi-product version of these equations presented in appendix A. Starting from initial equilibrium values $\left\{m_{jdt}^{(0)}, c_{jdt}^{(0)}, \lambda_{jdt}^{(0)}\right\}$ for markups, marginal costs and quality, 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:

$$\mathbb{P}_{jdt}^{(s)}(y, \nu) = \mathbb{P}_{jdt}(y, \nu, \boldsymbol{\delta}_{dt}^{(s)}, \boldsymbol{p}_{dt}^{(s)}; \boldsymbol{\theta})$$

  with $\delta_{jdt}^{(s)} = \beta x_{jdt} + \lambda_{jdt}^{(s)}$ and $\log p_{jdt}^{(s)} = \log m_{jdt}^{(s)} + \log c_{jdt}^{(s)}$

- Given these new probabilities, we recompute the optimal markup and quality levels chosen

[47]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.

by French firms:

$$m_{jdt}^{(s+1)} = 1 + \frac{1}{\int \exp(\alpha_i)\, \mathcal{E}_{jdt}^{(s)}(y,\nu)\, \omega_{jdt}^{(2,s)}(y,\nu)\, dy\, d\nu}$$

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

with $\tilde{\alpha}_{jdt}^{(s+1)} = \int \exp(\alpha_i)\, \omega_{jdt}^{(3,s)}(y,\nu)\, dy\, d\nu$ and

$$\omega_{jdt}^{(2,s)}(y,\nu) \equiv \frac{y\, \mathbb{P}_{jdt}^{(s)}(y,\nu)\, F(y)\, G(\nu)}{\int y\, \mathbb{P}_{j}^{(s)}(y,\nu)\, F(y)\, G(\nu)\, dy\, d\nu},$$

$$\omega_{jdt}^{(3,s)}(y,\nu) \equiv \frac{y\, \mathcal{E}_{jdt}^{(s)}(y,\nu)\, \mathbb{P}_{jdt}^{(s)}(y,\nu)\, F(y)\, G(\nu)}{\int y\, \mathcal{E}_{jdt}^{(s)}(y,\nu)\, \mathbb{P}_{jdt}^{(s)}(y,\nu)\, F(y)\, G(\nu)\, dy\, d\nu}.$$

- Finally, we update the marginal cost of production:

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

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}.[48] 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.

We report the results of this counterfactual experiment in figure 8. We report the log-change in market shares, markup, quality and profit from an increase in Chinese competition. Moreover, we emphasize the differences across outcomes in three scenarios: one without adjustment, similar to the previous subsection, one in which firms only adjust their markup and one in which they adjust markups and quality to their new optimal levels. We compare these outcomes across price deciles within a destination-HS6 market, using the tenth decile as normalization. Therefore, the black elements on the figure are similar to the ones described in the previous subsection, with a rise in Chinese competition that generates an additional 8 percent reduction in market share and profit for firms located in the first decile relative to the tenth one.

As a first source of adjustment, firms re-optimize their pricing strategy. On average, we find that French firms increase their markup by .6%: 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

[48] 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.

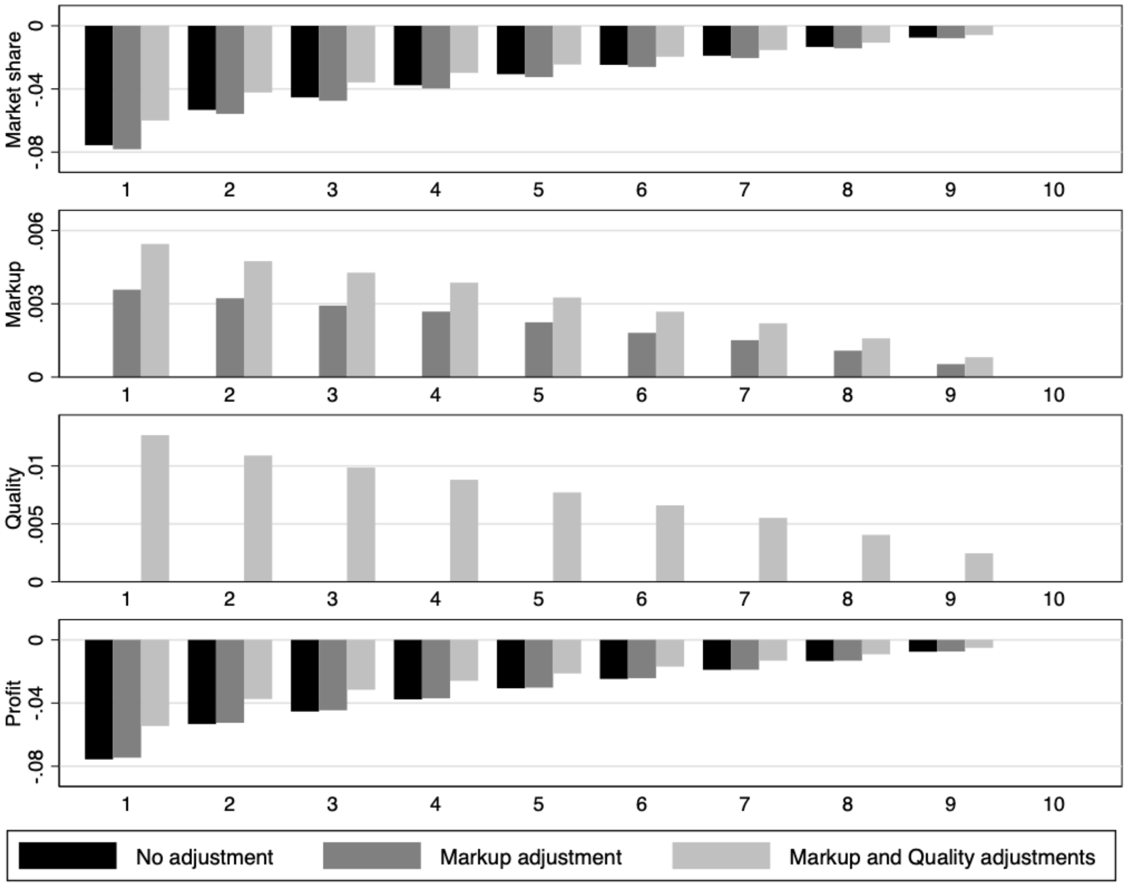

FIGURE 8: Effect of the China shock and the quality response

Notes: The figure reports the average log-change in market shares, markups, quality and profit for all French firms in 1997, separately for each price decile and relative to the top 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 under three scenarios. Price deciles are computed across French firms within a destination-HS6 market.

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.[49] As one can see from the dark grey elements on the figure, this adjustment is the largest at the bottom of the price distribution: assuming fixed quality, firms at the first decile increase their market by .4% on average relative to 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. Overall, this markup adjustment has a very limited impact at mitigating the shock for low-price firms: the heterogeneity in profit loss is essentially left unchanged across deciles.

The light gray elements of figure 8 show that quality adjustments play a more important role at mitigating the China shock across firms. On average, we find that firms increase their

[49]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.

quality by 1.5% and figure 8 shows that firms in the bottom price decile increase their quality twice more than the average firm: we measure an extra 1.3% by firms located in the first decile. 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 plays a significant role at reducing the heterogeneous impact of the China shock. While firms at the bottom of the price distribution records an extra 7.5% reduction in market share relative to the top decile, this gap is reduced to 5.5% when firms adjust their quality. Overall, quality upgrading can reduce one third of the unequal impact of Chinese competition.

These results highlight an important quality response that helps mitigate some of the additional impact that low-price firms face as a result of higher exposure to Chinese competition. However, we still find important differences in terms of outcome along the quality ladder: the cost of quality upgrading is large enough that firms still suffer significant losses despite the possibility of upgrading their product quality. It tends to indicate that this mechanism offers some relief for firms aiming at mitigating the adverse effects of low-cost countries competition. In conclusion, while quality adjustments help low-quality firms mitigate the China shock, the heterogeneous effects of this shock remain large and heterogeneous across firms.

7 Conclusion

In this paper, we quantify the heterogeneous impact of foreign competition along the quality ladder. To achieve this, we estimate a random-coefficient nested logit (RCNL) demand system. This model allows us to incorporate nested preferences across product categories and country of origin, and a price elasticity that varies across consumers to generate 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 firms located at the bottom of the price distribution saw an additional 8 percent decrease in market shares and profit from the rise of Chinese competition, relative to the top decile. This heterogeneous impact along the price distribution is as large as half of the differentiated impact generated by horizontal differentiation. We find that quality upgrading helps firms mitigate this heterogenous impact, but only to a limited extend.

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 important adjustment costs that these investments entail.

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Appendices

A Theory Appendix

In this appendix, we start by deriving the derivatives of the purchasing probability with respect to the common utility shifter. Then, we detail the optimality conditions of a firm in the case of multi-products. Finally, we explicit the iterative algorithm used in the counterfactual experiment.

Market share derivatives An important object in the model is the purchasing probability $\mathbb{P}_{ij}$ defined as

$$\mathbb{P}_{ij} = \mathbb{P}_i^{j|og} \times \mathbb{P}_i^{o|g} \times \mathbb{P}_i^{g} = \frac{\exp\left(\frac{\delta_j+\mu_{ij}}{1-\rho_1}\right)}{\exp\left(\frac{I_{iog}}{1-\rho_1}\right)} \times \frac{\exp\left(\frac{I_{iog}}{1-\rho_2}\right)}{\exp\left(\frac{I_{ig}}{1-\rho_2}\right)} \times \frac{\exp(I_{ig})}{\exp(I_i)} \tag{21}$$

with

$$\begin{aligned}
I_{iog} &= (1-\rho_1)\log \sum_{k\in\mathcal{J}_{og}} \exp\left(\frac{\delta_k+\mu_{ik}}{1-\rho_1}\right),\\
I_{ig} &= (1-\rho_2)\log \sum_{o\in\mathcal{O}_{g}} \exp\left(\frac{I_{iog}}{1-\rho_2}\right),\\
I_i &= \log\left(1+\sum_{g\in\mathcal{G}} \exp\left(I_{ig}\right)\right).
\end{aligned}$$

The optimal choices of the firm in terms of prices and quality depend on the derivative of $\ln \mathbb{P}_{ij}$ with respect to the common utility shifter δ_k, defined as $\mathcal{E}_{ijk}$. This term is equal to

$$\mathcal{E}_{ijk} = \frac{\partial \ln \mathbb{P}_{ij}}{\partial \delta_k} = \frac{\partial \ln \mathbb{P}_i^{j|og}}{\partial \delta_k} + \frac{\partial \ln \mathbb{P}_i^{o|g}}{\partial \delta_k} + \frac{\partial \ln \mathbb{P}_i^{g}}{\partial \delta_k}$$

with

$$\frac{\partial \ln \mathbb{P}_i^{j|og}}{\partial \delta_k} = \begin{cases} \frac{1}{1-\rho_1}\left(1-\mathbb{P}_{im}^{k|og}\right) & \text{if } k=j\\ -\frac{1}{1-\rho_1}\mathbb{P}_i^{k|og} & \text{if } k\neq j \text{ but } k \text{ is in the same segment-origin nest as } j\\ 0 & \text{if } k \text{ is not the same segment-origin as } j, \end{cases}$$

$$\frac{\partial \ln \mathbb{P}_i^{o|g}}{\partial \delta_k} = \begin{cases} \frac{1}{1-\rho_2}\mathbb{P}_i^{k|og}\left(1-\mathbb{P}_i^{o|g}\right) & \text{if } k \text{ is in the same segment-origin nest as } j\\ -\frac{1}{1-\rho_2}\mathbb{P}_i^{k|o^*g}\mathbb{P}_i^{o^*|g} & \text{if } k \text{ is in the same segment as } j \text{ but has a different origin } o^*\\ 0 & \text{if } k \text{ is not in the same segment as } j, \end{cases}$$

$$\frac{\partial \ln \mathbb{P}_i^{g}}{\partial \delta_j} = \begin{cases} \mathbb{P}_i^{k|o^*g}\mathbb{P}_i^{o^*|g}\left(1-\mathbb{P}_i^{g}\right) & \text{if } j \text{ and } k \text{ are in the same product segment}\\ -\mathbb{P}_{ik} & \text{if } k \text{ is not in the same segment as } j. \end{cases}$$

Therefore, we have

$$
\mathcal{E}_{ijk} = \begin{cases} \frac{1}{1-\rho_1} + \frac{\rho_2-\rho_1}{(1-\rho_1)(1-\rho_2)}\mathbb{P}_i^{k|og} - \frac{\rho_2}{1-\rho_2}\mathbb{P}_i^{k|g} - \mathbb{P}_{ik} & \text{if } k = j \\ \frac{\rho_2-\rho_1}{(1-\rho_1)(1-\rho_2)}\mathbb{P}_i^{k|og} - \frac{\rho_2}{1-\rho_2}\mathbb{P}_i^{k|g} - \mathbb{P}_{ik} & \text{if } k \neq j \text{ but } k \text{ is in the same segment-origin nest as } j \\ -\frac{\rho_2}{1-\rho_2}\mathbb{P}_i^{k|g} - \mathbb{P}_{ik} & \text{if } k \text{ is in the same segment but has a different origin} \\ -\mathbb{P}_{ik} & \text{if } k \text{ is not in the same segment as } j \end{cases}
$$

Profit maximization in the case of a multi-products firm We can now move to the derivations of the optimal conditions associated with the firm's problem. We assume the existence of a Nash-Bertrand equilibrium, so that each producer $f = 1, \cdots, F$ chooses simultaneously its prices and qualities for its different varieties in order to maximize its total profit, given other firms' decisions. The total profit function of producer f is

$$
\Pi_f(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{k \in \mathcal{J}_f} \pi_k(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{k \in \mathcal{J}_f} r_k(\boldsymbol{\lambda}, \boldsymbol{p}) \cdot \left(1 - \frac{c_k(\lambda_k)}{p_k}\right), \tag{22}
$$

with $\mathcal{J}_f$ the set of varieties supplied by producer f.

Optimal pricing When choosing their prices p_j, producers take into account cannibalization across varieties, the set of first order conditions for each price p_j of producer f is the following:

$$
\begin{aligned}
\sum_{k \in \mathcal{J}_f} \frac{\partial \pi_k}{\partial p_j} = 0\,, \quad \forall j \in \mathcal{J}_f \qquad & \Leftrightarrow \quad r_j \frac{c_j}{p_j^2} + \sum_{k \in \mathcal{J}_f} \frac{\partial r_k}{\partial p_j} \cdot \left(1 - \frac{c_k}{p_k}\right) = 0\,, \quad \forall j \in \mathcal{J}_f \\
& \Leftrightarrow \quad \frac{c_j}{p_j} + \sum_{k \in \mathcal{J}_f} \frac{\partial r_k}{\partial \ln p_j} \frac{1}{r_j} \cdot \left(1 - \frac{c_k}{p_k}\right) = 0\,, \quad \forall j \in \mathcal{J}_f
\end{aligned}
$$

These first-order conditions can be rewritten in vectorized form, by stacking up the first order conditions across all varieties in a market:

$$
\boldsymbol{M} - \boldsymbol{\Delta}(1 - \boldsymbol{M}) = 0\,, \tag{23}
$$

where $\boldsymbol{M} = \left[\frac{c_j}{p_j}\right]$ is a column-vector of size $J+1$ which contains inverse multiplicative markups. $\boldsymbol{\Delta} = [\Delta_{j,k}]$ is the matrix of size $(J+1) \times (J+1)$ whose coefficient (j,k) verifies

$$
\Delta_{j,k} \equiv \begin{cases} -\frac{\partial r_k}{\partial \ln p_j} \frac{1}{r_j} & \text{if } j \text{ and } k \text{ belong to the same firm,} \\ 0 & \text{otherwise,} \end{cases} \quad ,
$$

and $\frac{\partial r_k}{\partial \ln p_j}\frac{1}{r_j}$ verifies :

$$\begin{aligned}
\frac{\partial r_k}{\partial \ln p_j}\frac{1}{r_j} &= \frac{\partial}{\partial \ln p_j}\left(\int \mathbb{P}_k(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu\right)\frac{1}{r_j} \\
&= \frac{\int \frac{\partial \mathbb{P}_k(y,\nu)}{\partial \ln p_j}\, y\, F(y)\, G(\nu)\, dy\, d\nu}{\int \mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu} \\
&= -\frac{\int \exp(\alpha(y,\nu))\frac{\partial \ln \mathbb{P}_k(y,\nu)}{\partial \delta_j}\, \mathbb{P}_k(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu}{\int \mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu} \\
&= -\int \exp(\alpha(y,\nu))\mathcal{E}_{k,j}(y,\nu)\, \omega^{(2)}_{k,j}(y,\nu) dy\, d\nu,
\end{aligned}$$

with $\omega^{(2)}_{k,j}(y,\nu) \equiv \frac{\mathbb{P}_k(y,\nu)\, y\, F(y)\, G(\nu)}{\int \mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu}$ the share of consumer i in the revenues of the variety.

In the special case where firms are single-variety, they only care about the diagonal terms of the matrix $\boldsymbol{\Delta}$, so that the optimal pricing rule becomes:

$$\frac{p_j}{c_j} = 1 + \frac{1}{\Delta_{jj}} = 1 + \frac{1}{\int \exp(\alpha(y,\nu))\, \mathcal{E}_j(y,\nu)\, \omega^{(2)}_j(y,\nu)\, dy\, d\nu}\,.$$

Optimal quality The firm's first order condition with respect to quality can be written as follows:

$$\begin{aligned}
\sum_{k\in\mathcal{J}_f}\frac{\partial \pi_k}{\partial \lambda_j} = 0\,, \quad \forall j \in \mathcal{J}_f \qquad &\Leftrightarrow \quad -\frac{r_j}{p_j}\frac{\partial c_j}{\partial \lambda_j} + \sum_{k\in\mathcal{J}_f}\frac{\partial r_k}{\partial \lambda_j}\left(1 - \frac{c_k}{p_k}\right) = 0\,, \quad \forall j \in \mathcal{J}_f \\
&\Leftrightarrow \quad -\frac{c_j}{p_j}\frac{\partial \ln c_j}{\partial \lambda_j} + \sum_{k\in\mathcal{J}_f}\frac{\partial r_k}{\partial \lambda_j}\frac{1}{r_j}\left(1 - \frac{c_k}{p_k}\right) = 0\,, \quad \forall j \in \mathcal{J}_f \\
&\Leftrightarrow \quad \frac{\partial \ln c_j}{\partial \lambda_j} = -\frac{\sum_{k\in\mathcal{J}_f}\frac{\partial r_k}{\partial \lambda_j}\frac{1}{r_j}\left(1-\frac{c_k}{p_k}\right)}{\sum_{k\in\mathcal{J}_f}\frac{\partial r_k}{\partial \ln p_j}\frac{1}{r_j}\cdot\left(1-\frac{c_k}{p_k}\right)}\,, \quad \forall j \in \mathcal{J}_f \\
&\Leftrightarrow \quad \frac{\partial \ln c_j}{\partial \lambda_j} = \frac{\boldsymbol{G}^j(1-\boldsymbol{M})}{\boldsymbol{\Delta}^j(1-\boldsymbol{M})}\,, \quad \forall j \in \mathcal{J}_f
\end{aligned}$$

where $\boldsymbol{G} = [G_{jk}]$ is the matrix of size $(J+1)\times(J+1)$ whose coefficient (j,k) verifies

$$G_{jk} \equiv \begin{cases} -\frac{\partial r_k}{\partial \lambda_j}\frac{1}{r_j} & \text{if } j \text{ and } k \text{ belong to the same firm,} \\ 0 & \text{otherwise,} \end{cases}$$

and $\boldsymbol{\Delta}^j$ and $\boldsymbol{G}^j$ respectively denote the j-th row of $\boldsymbol{\Delta}$ and $\boldsymbol{G}$.

The term $-\frac{\partial r_k}{\partial \lambda_j}\frac{1}{r_j}$ can be written

$$
\begin{aligned}
-\frac{\partial r_k}{\partial \lambda_j}\frac{1}{r_j} &= -\frac{\partial}{\partial \lambda_j}\left(\int \mathbb{P}_k(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu\right)\frac{1}{r_j} \\
&= -\frac{\int \frac{\partial \mathbb{P}_k(y,\nu)}{\partial \lambda_j}\, y\, F(y)\, G(\nu)\, dy\, d\nu}{\int \mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu} \\
&= -\frac{\int \frac{\partial \ln \mathbb{P}_k(y,\nu)}{\partial \delta_j}\, \mathbb{P}_k(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu}{\int \mathbb{P}_j(y,\nu)\, y\, F(y)\, G(\nu)\, dy\, d\nu} \\
&= -\int \mathcal{E}_{k,j}(y,\nu)\, \omega^{(2)}_{k,j}(y,\nu) dy\, d\nu,
\end{aligned}
$$

Given our specification of the marginal costs of production in equation (11), the optimal quality can be written

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

In the case of a single-product firm, we find that the optimal quality is

$$
\begin{aligned}
\lambda_j^* = \frac{1}{2h}\left(\tilde{\alpha}_j^{-1} - \eta_j\right) \quad \text{with} \quad \tilde{\alpha}_j = \frac{\Delta_{jj}}{G_{jj}} &= \frac{\int \exp(\alpha(y,\nu))\mathcal{E}_j(y,\nu)\, \omega_j^{(2)}(y,\nu) dy\, d\nu}{\int \mathcal{E}_j(y,\nu)\, \omega_j^{(2)}(y,\nu) dy\, d\nu} \\
&= \int \exp(\alpha(y,\nu))\, \omega_j^{(3)}(y,\nu) dy\, d\nu
\end{aligned}
$$

and $\omega_j^{(3)}(y,\nu) = \frac{\mathcal{E}_j(y,\nu)\, \omega_j^{(2)}(y,\nu)}{\int \mathcal{E}_j(y,\nu)\, \omega_j^{(2)}(y,\nu) dy\, d\nu}$.

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 (14) 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 (11) 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 8 summarizes the classification of countries as used in the paper.

TABLE 8: Country classification

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

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

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

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

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

In order to 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,[50] 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".

Shoe sample The estimation of the model is implemented for the footwear industry. Specifically, we focus on all the HS6 category belonging to the HS4 ranging from 6400 to 6405. This means including all product categories of Footwears, except the heading 6406 that corresponds to parts of footwear. In order to maintain a consistent classification, we merge the product categories 640199 and 640191; 640291, 640230 and 640299; and 640391, 640330 and 640399. This leaves us with a total of 20 product categories at the HS6 level that we will defines as segment or category in the text.

Constructing Prices We use unit values - the ratio between the value and the weight of a trade flow - as a proxy for prices. We use FOB prices in section 2 since our empirical strategy only requires us to compare prices across French firms. However, when estimating the demand system developed in section 3, 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 and 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

[50] 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.

country, CPA level by taking the average over the period of the ratio between transportation costs and FOB trade.

Tariffs data We use a combination of source to construct tariffs data for shoes at the hs6-destination-origin-year level. First, we use the applied tariff measure constructed by the WTO and accessible from the WITS website. We supplement this measure by the tariff measure provided by Trains. When using Trains, we use the preferential measure if available and the MFN tariffs otherwise. Finally, to complete missing information at the bilateral level, we complete these measures with the Market Access Map (MAcMap) dataset provided by the CEPII. In its public version, it provides information about the bilateral tariffs rates applied at the HS2 level. For our application, we use tariffs applied to the HS2 code 64: "Footwear; gaiters and the like; Parts of such articles". Since the dataset only provides applied tariffs for the year 2001, 2004 and 2007, we apply the 2001 tariffs to the 1997-2002 period, the 2004 tariffs to the 2003-2005 period and the 2007 tariffs to the 2006-2010 period.

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

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

with $\ln p_{sdpt}$ the log export price of a country s exporting HS6+ product p to destination country d. For observations such that the error term $\hat{e}_{sdpt}$ is larger than 2 in absolute value, we substitute the actual price $\ln p_{sdpt}$ with predicted price $\ln \hat{p_{sdpt}} = FE_{sd} + FE_t + FE_p$. 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 do not cross a border. In order to proxy the price of the domestic good in a given country and year, we use the price of its exports as measured in the BACI dataset. However, since we observe this price for many destinations, we infer the domestic unit values by regressing the logarithm of the FOB unit value on a set of fixed effects:

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

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

$$\ln \hat{p}_{st} = \hat{FE}_{st}^{(1)}.$$

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 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 results may suffer from an aggregation bias. In this appendix, we investigate this possibility by simulating the existence of several producers from each origin country (except for France, for which we use the actual firm-level data), 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.[51] 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.

We re-run our counterfactual experiments using the obtained dataset. Figure 9 reports the impact of bringing the fundamentals of all Chinese firms to their post-2007 values. We find little difference between these results and the ones using the aggregated sample reported in figure 8. We still find that French firms are differently affected by Chinese competition, and that – to a limited extent – quality upgrading helps low-price French firms mitigate this adverse shock. This is reassuring that the absence of disaggregated data does not strongly affect the conclusions of our paper.

[51] 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.

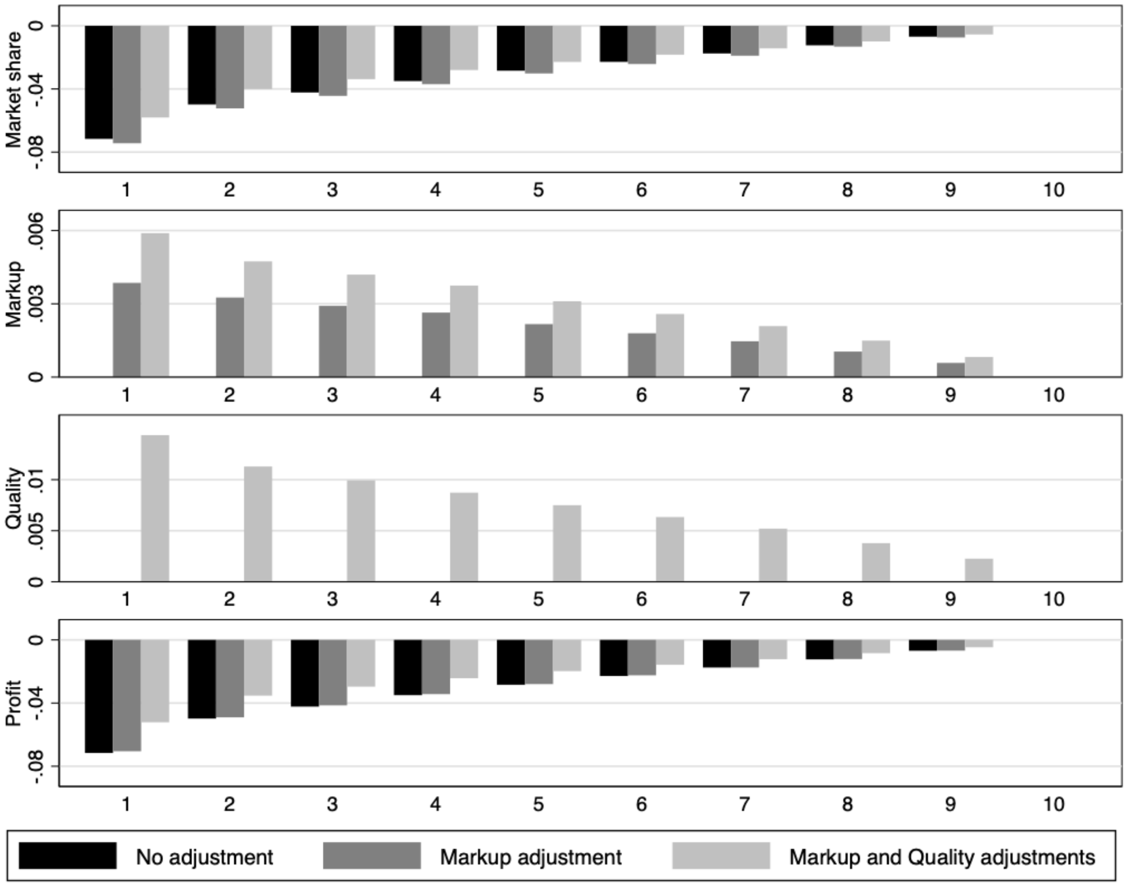

FIGURE 9: Effect of the China shock (disaggregated data)

Notes: The figure reports the average log-change in market shares, markups, quality and profit for all French firms in 1997, separately for each price decile and relative to the top 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 under three scenarios. The effects are computed using the simulated disaggregated data (see text for details). Price deciles are computed across French firms within a destination-HS6 market.

D Additional Results

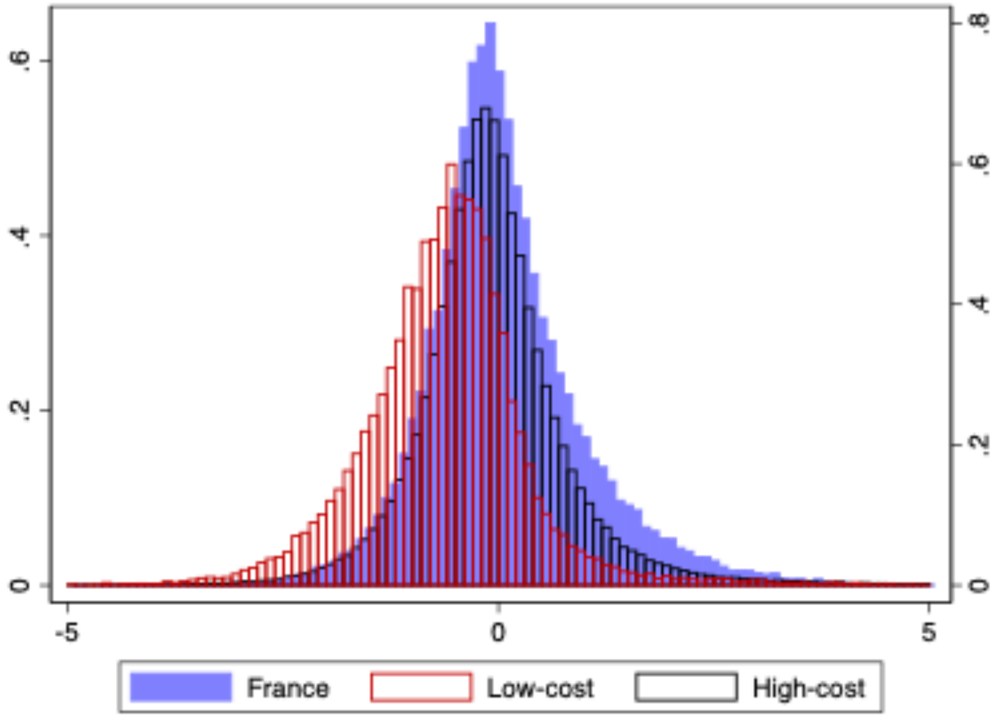

FIGURE 10: Distribution of Export prices

Notes: This figure shows the distribution of FOB export prices in 2000, expressed in log-difference to the mean price in the destination-HS6 market. Each observation is weighted by its market share in the destination-HS6 market.

Table 9: High-price varieties suffer less from Chinese competition

Dependent variable:	*log export*		*Survival*	
	(1)	(2)	(3)	(4)
2nd price quartile	-0.18***	.	0.012***	.
	(0.01)		(0.0008)	
3rd price quartile	-0.23***	.	0.021***	.
	(0.01)		(0.0008)	
4th price quartile	-0.14***	.	0.0049***	.
	(0.009)		(0.0008)	
Chinese penetration				
× 2nd price quartile	0.60***	0.22***	0.026***	0.078***
	(0.05)	(0.05)	(0.005)	(0.01)
× 3rd price quartile	0.79***	0.29***	0.036***	0.12***
	(0.05)	(0.05)	(0.005)	(0.01)
× 4th price quartile	1.02***	0.25***	0.053***	0.13***
	(0.05)	(0.05)	(0.005)	(0.01)
N	5 289 247	5 134 246	5 076 541	4 931 791
R^2	0.27	0.83	0.13	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, *** p<0.001.

Table 10: Estimation results: supply side (using differences)

	$\Delta\lambda_{jdt}$			$\Delta \log mc_{jdt}$			*Stacked*		
$\Delta\tilde{\alpha}^{-1}$	1.82***	1.90***	1.90***						
	(0.2)	(0.4)	(0.6)						
$\Delta(\tilde{\alpha}^{-1})^2$				0.99***	0.98***	1.03***			
				(0.09)	(0.2)	(0.2)			
$\Delta\breve{\alpha}^{-1}$ or $\Delta\frac{(\breve{\alpha}^{-1})^2}{2}$							1.91***	1.93***	1.99***
							(0.2)	(0.3)	(0.5)
Diff. length	1 y.	3 y.	5 y.	1 y.	3 y.	5 y.	1 y.	3 y.	5 y.
$\hat{h}$	0.27	0.26	0.26	0.25	0.26	0.24	0.26	0.26	0.25
N	82 254	38 103	19 523	82 254	38 103	19 523	164 508	76 206	39 046
R^2	0.32	0.39	0.41	0.076	0.099	0.13	0.26	0.30	0.32

Notes: Firm-level clustered standard errors between parentheses. All regressions include destination-HS6-year fixed effects.

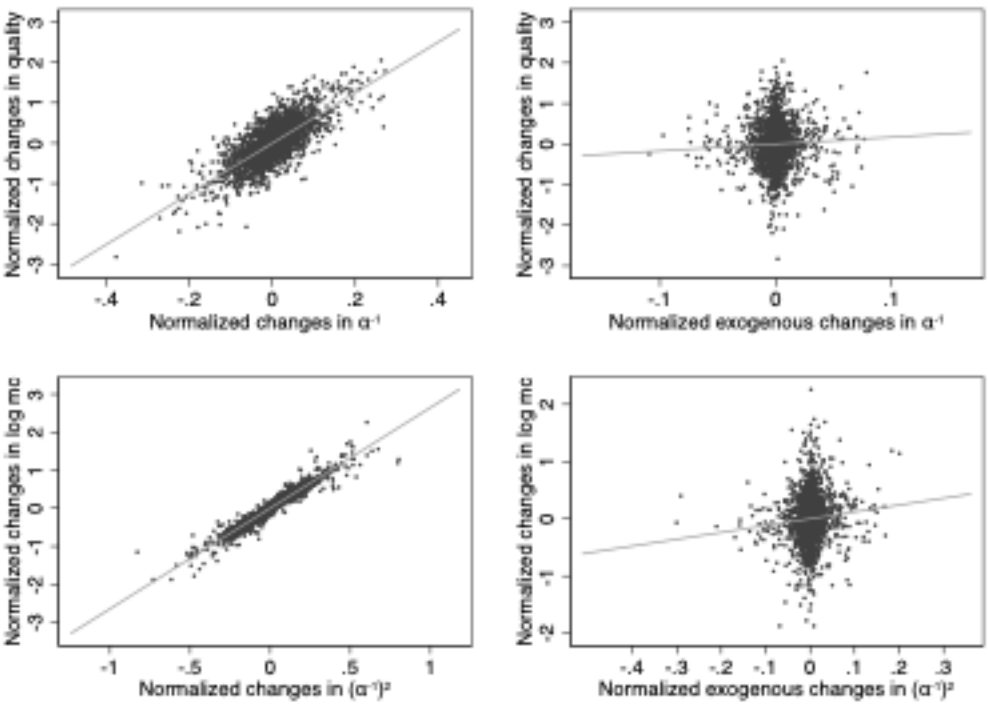

FIGURE 11: Estimation of the convexity of the marginal cost function

Notes: These figures show the scatterplot associated with the regressions estimated in table 6. Each variable is demeaned using firm×HS6×destination and HS6×destination×year fixed effects to obtained a "normalized change" in each of these variables.