Foreign Competition along the Quality Ladder*

Paul Piveteau[†]

Gabriel Smagghue[‡]

February 2022

Abstract

We document that firms with low prices are more impacted by the rise of low-cost competition, even within narrowly defined product categories. To explain this pattern, 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 heterogeneous impact of the shock.

*We are grateful to Amit Khandelwal, Houssein Guimbard, Thierry Mayer, John Morrow, Eric Verhoogen, David Weinstein and seminar and conference audiences at Johns Hopkins, Columbia, Carlos 3, Kent, Birkbeck universities, the Bank of Italy, ETSG 2017, EIIT 2017, SED 2018, RMET 2019 and the Midwest International Trade Conference 2018 for numerous comments and discussions. We also thank the CEPII for providing data access. This paper was previously circulated under the title "The Impact of Chinese Competition along the Quality Ladder". We thank CNIS and French customs for confidential data access.

[†]School of Advanced International Studies, Johns Hopkins University. 1717 Massachusetts Avenue NW. Washington DC, 20036. Email: ppiveteau@jhu.edu

[‡]Bank of France. Email: gabriel.smagghue@banque-france.fr

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.

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.

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 more than 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 trade data from France, we show that French exporters with low prices had lower performance records in foreign markets where the import penetration from low-cost countries increased. Specifically, they display larger reductions in exported values and participation 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. Altogether, French exporters appear more affected by competing firms that resemble them. Moreover, we find that increasing low-cost competition is also associated with price adjustments: when low-cost competition intensifies, exporters with low prices – which are more affected by low-cost competition – increase their price relative to high price exporters.[1]

Based on this body of 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 both 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. It allows us to estimate specific substitution patterns between varieties in the same product category or from the same origin country. 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, 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 the values and prices of exports to 38 destination countries.[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 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

[1] We establish these results for exporters in foreign markets, since we do not observe the price of French firms on their domestic market.

[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 transportations costs and the domestic penetration rate in these destinations, which will be used as outside good in our model.

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. However, the use of international trade data also comes with a cost: while we use firm-level data from France, this level of aggregation is not available for other exporting countries. As a result, we treat each other country as a single exporter, and show that our results do not appear to be sensitive to this approximation.

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 80 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 closer to 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 these firm-level estimates, we are able to estimate the supply side of the model, and notably the cost of quality upgrading. To this end, we first infer marginal costs from (estimated) markups and (observed) prices, and estimate the cost of quality, i.e. the causal impact of quality on marginal costs. However, estimating this relationship 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 isolate changes in quality and marginal costs generated by a change in competition only, holding characteristics of the firm constant: changes in the competitive environment alter the set of residual consumers faced by a French firm. As a result, the average price-elasticity faced by the firm changes, which modifies its optimal quality. For instance, French firms face higher incentives to produce high-quality products as low-cost producers gain market shares and capture price-elastic consumers. As firms adjust their product quality in response to these exogenous factors, we can measure the associated changes in marginal costs, which consistently identifies the cost of producing higher quality products.

Using outcomes from the demand estimation, and before estimating the supply-side, 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 competition-induced (exogenous) changes in the average price elasticity: as competition reallocates consumers between varieties, firms losing price-elastic consumers tend to optimally increase their quality and their marginal cost. The magnitude of this response 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 shares of firms located at the bottom decile of the price distribution decrease by an additional 10 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 heterogeneous 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 heterogeneous 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 RCNL similar to 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 et al. (2021) 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

[4]We find that within a destination market, the nested logit model, capturing horizontal differentiation, can explain almost 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 liberalization along the quality ladder. By contrast, we are the first to estimate a random coefficient demand system to study how vertical differentiation shapes the firm-level impact of trade. Moreover, we add to the many studies linking trade and quality decisions. Amiti and Khandelwal (2013) documents the quality response to import competition using country-level data. Different channels have been documented to explain the relationship between trade and quality, e.g. better access to high quality inputs (Fieler, Eslava, and Xu, 2018; Bas and Strauss-Kahn, 2015); better access to destination markets with a high demand for quality (Verhoogen, 2008; Bastos, Silva, and Verhoogen, 2018). We contribute to this literature by showing that within product-destination markets, foreign competition can impact firms' quality decisions by changing the income composition of their residual consumers. Relatedly, Medina (2020) 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 (2021) and Hottman and Monarch (2020) 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 (2021) 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 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] Because this dataset does not contain information on the domestic sales and prices of French firms, our analysis focuses on the performance of French firms in foreign destinations. 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, 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), rather than in kilos. For instance, the USUP for liquids is the volume in liters. By contrast, BACI only uses weights 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 at the product level from USUP to kilos based on flows for which both weight and USUP are declared. We use this conversion rate to assign a weight to observations where only the USUP is declared. See appendix A for details on this procedure.

As is common in the trade literature, we use unit values – the ratio between the value and the weight of a trade flow – as a proxy for prices. Because unit values in trade data are known to be noisy, we exclude observations for which the log-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.[9] Finally, because the empirical model will require information about destination markets, we limit our sample to 38 destinations from the World

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

Input-Output Database (WIOD).[10]

Our final dataset combines bilateral export 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 40 million observations, around 16.5 million of them from individual French firms. In the next section, we use this dataset to document the co-movements between firm-level French exports and foreign competition.

2.2 Stylized Facts

In this section, we show that French exporters located at different positions in the price distribution are differently affected by foreign competition. We start this section by defining the econometric specification and identification strategy, before showing the differential impact of foreign competition on export performance and prices.

Econometric Specification In order to highlight the heterogeneous effects of foreign competition, we start by classifying French exporters according to their position in the price distribution. To this end, we project the logarithm of the unit value before 2001 on a set of firm-HS6-destination and HS6-destination-year fixed effects:[11]

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

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 market share of exports originating from low-cost countries[12] – MSL_{dpt} – and estimate how individual exporters are differently affected by the change in this market share. Specifically, we estimate the following regression:

$$Y_{fdpt} = \sum_{q=1}^{4} \delta_q \mathbb{1}\{PQ_{fpd} = q\} \times MSL_{dpt} + \text{FE}_{pdt} + \text{FE}_{fpd} + \varepsilon_{fpdt}, \tag{2}$$

where Y_{fdpt} is a measure of export performance, either the logarithm of export values, the logarithm of export prices or an export participation dummy. We interact the market share MSL_{dpt} with a full set of dummies for each value of price quartile 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,

[10] 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.

[11] We use the beginning-of-period unit values to guarantee that firms' position along the price distribution is not endogenous to the growth of foreign competition over the period. We classify firms based on the first four years of the sample (1997-2000) in order to mitigate measurement errors that might arise from using only one year of observation.

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

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 time 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.

Identification Strategy We want to identify the impact on French firms of changes in MSL_{dpt} resulting from supply shocks in low-cost countries. For instance, we want the import penetration of low-cost countries to grow in the toy industry because these countries become more competitive in this industry over the period. The problem is that in the data, this growth may also be driven by an increase in the demand for low-quality toys or by a negative productivity shock faced by some toy producers in the destination market. Even though our empirical setting focuses on the performance of French firms in foreign destinations, which limits the risk of reverse causality between French performance and low-cost countries growth, an identification based on external supply shocks is better suited for our exercise.

In order to isolate relevant variation in MSL_{dpt}, we follow a strategy similar to Autor et al. (2014), by identifying product-specific growth in destinations not included in our primary dataset. Namely, we estimate the following regression:

$$MSL_{dpt} = \alpha_{pt} + \alpha_{dt} + \varepsilon_{fpdt}, \tag{3}$$

where α_{pt} and α_{dt} are respectively $HS6+ \times$ year fixed effects and destination $\times$ year fixed effects. We estimate this regression using only observations from destinations that are not included in the WIOD dataset, so that the fixed effects α_{pt} captures product-level growths of low-cost countries in destinations that are not used in the main estimation. Then, we estimate our equation of interest – equation (2) – by two stage least squares using $\mathbb{1}\{PQ_{fpd} = q\} \times \alpha_{pt}$, $q = 1, \cdots, 4$ as instrumental variables for $\mathbb{1}\{PQ_{fpd} = q\} \times MSL_{dpt}$, $q = 1, \cdots, 4$. Because regressions (2) and (3) are estimated on two non-overlapping sets of destination countries, our identification comes from product-year specific supply shocks which drive the co-movement of low-cost penetration throughout destination markets.

Low-cost competition and firm-level French exports The heterogeneous impacts of low-cost competition on French export performance is reported in table 1.[13] In all specifications, the first price quartile is used as omitted category, such that all coefficients must be interpreted relative to firms located in this group. In column (1), we report the effect on exported values estimated by OLS. The coefficients related to the interaction terms are all positive, which imply that high-price firms suffer a lower reduction in their exports when low-cost market shares increase. When instrumenting low-cost penetration in column (2), we find a larger magnitude for our estimates, although they are less precisely estimated.[14] For an exporting firm, a 10

[13] 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.

[14] The fact that the magnitude of the estimated coefficient is larger with 2SLS suggests that the OLS estimates are biased by unobserved demand shocks. To the extent that demand shocks faced by low-cost countries are more positively correlated to demand shocks on cheap French varieties than on expensive French varieties, unobserved

points increase in the market share of low-cost countries leads to an additional 3.2% reduction in exports for a firm in the first price quartile relative to a firm in the second.

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

Dependent variable:	*log export*		*Exp. participation*	
Estimator:	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Low-cost penetration				
× 2nd price quartile	0.16***	0.32**	0.030***	0.057***
	(0.06)	(0.15)	(0.007)	(0.02)
× 3rd price quartile	0.22***	0.39**	0.047***	0.13***
	(0.06)	(0.16)	(0.008)	(0.02)
× 4th price quartile	0.18**	0.12	0.075***	0.22***
	(0.07)	(0.2)	(0.008)	(0.02)
N	6 268 551	6 268 551	13 747 041	13 747 041
First stage F-stat		407.7		602.7

Notes: Standard errors clustered at the HS6+ level, between parentheses. All specifications include product-destination-year and firm-product-destination fixed effects. Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

In columns (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 is a dummy equal to one if trade flow fpd is active in t. To estimate this regression, we create zeros in the data for any trade flow that is missing in a given year but was active at least once between 1997 and 2000. Results on selection 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 participation rate of low-price firms decreases by 2.2 percentage points relative to firms in the top price quartile. In appendix B, we investigate the robustness of our reduced form evidence. First, in table 9 we show that similar patterns hold when looking at the impact of Chinese competition only. Second, in table 11 we document that our results are not driven by interdependencies in firm decisions across product/destination markets.

Overall, table 1 suggests that low-price varieties are in closer competition to products from 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.[15] Results displayed in table 2 show that high-price firms are more affected by an increase in competition from high-cost countries both at the intensive and at the extensive margin.

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

demand shocks bias the coefficients downward.

[15]Once again, we rely on the classification from the World Bank to categorize a country as high-cost. See table 8 in appendix A for the detailed list. The instrument for high-cost penetration is obtained similarly to the instrument for low-cost competition: we regress high-wage market shares on product-year fixed effects and on destination-year fixed effects excluding the same 38 destinations.

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

Dependent variable:	*log export*		*Exp. participation*	
Estimator:	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
High-cost penetration				
× 2nd price quartile	-0.074*	-0.37**	-0.019***	-0.055**
	(0.04)	(0.17)	(0.006)	(0.02)
× 3rd price quartile	0.045	-0.47***	-0.020***	-0.14***
	(0.04)	(0.17)	(0.006)	(0.02)
× 4th price quartile	0.059	-0.14	-0.036***	-0.25***
	(0.05)	(0.2)	(0.007)	(0.03)
N	6 268 551	6 268 551	13 747 041	13 747 041
First stage F-stat		257.3		304.8

Notes: Standard errors clustered at the HS6+ level, between parentheses. All specifications include product-destination-year and firm-product-destination fixed effects. Significance levels: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

in the product space, and in particular in the price distribution, display stronger substitution patterns. Figure 9 in the appendix B supports this hypothesis: it shows that prices of varieties from developing countries are closer to those of low-price French exporters than those of high-price French exporters.

Low-cost competition and the price of French varieties Having shown the heterogeneous impact of low-cost competition, we now investigate whether firms responded differently to the rise of competition from low-cost countries. In particular, we look in table 3 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 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 to 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 this 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.

Table 3: Price responses to low-cost competition

Dependent variable:	*log price*	
Estimator:	OLS	2SLS
	(1)	(2)
Low-cost penetration		
× 2nd price quartile	-0.60***	-1.92***
	(0.04)	(0.09)
× 3rd price quartile	-0.92***	-3.34***
	(0.05)	(0.1)
× 4th price quartile	-1.56***	-5.57***
	(0.010)	(0.22)
N	6 268 551	6 268 551
First stage F-stat		407.7

Notes: Standard errors clustered at the HS6+ level, between parentheses. All specifications include product-destination-year and firm-product-destination fixed effects. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

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 heterogeneity in consumer preferences with a nested structure in the error term of the model. This demand system allows us to estimate specific substitution patterns between varieties belonging to the same product group but also captures realistic competition effects along the quality ladder. Moreover, 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.

On the supply side, firms choose the price and quality of their products. The presence of heterogeneous consumers on the demand side has important implications for price and quality choices: mark-ups are positively correlated with quality, and quality responds to a change in the competitive environment. Accounting for these decisions in the firms' problem allows us to quantify the role of these responses in mitigating competition shocks. However, we do not model the endogenous entry and exit of firms. Estimating an entry model with random-coefficients demand is a fruitful avenue for future research, but is beyond the scope of this paper.[16]

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

[16]Even controlling for selection through a reduced-form selection equation, which is arguably less challenging than estimating a structural model of entry, has only been recently tackled by the empirical IO literature. To our knowledge, only two recent papers – Dubé et al. (2021) and Gandhi et al. (2020) – have started studying the question of zeros in the context of random-coefficients model. We discuss some attempts at controlling for endogenous selection in appendix D.

choice made by producers.

3.1 Demand Side

Preferences The global economy is a collection of markets, defined as an industry×destination country×year triplet, each populated with a continuum of heterogeneous consumers. Within these markets, 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

$$u_{ij} = q_{ij}^{\exp(\alpha_i)} \exp\left(\delta_j + \bar{\epsilon}_{ij}\right) \quad j = 0, \cdots, J. \tag{4}$$

This formulation of the utility function reveals that the consumer cares about the quantity q_{ij} she consumes, as well as 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 raise 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 drive the price elasticity of each consumer. In the extreme case where $\alpha \to +\infty$, only quantity matters and the consumer is very sensitive to prices. 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:

$$\delta_j = \beta x_j + \gamma_{g(j)} + \underbrace{\gamma_{f(j)} + \xi_j}_{\text{Quality } \lambda_j}, \tag{5}$$

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 with international trade data, 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

$$\bar{\epsilon}_{ij} = \zeta^1_{ig(j)} + (1-\rho_2)\zeta^2_{igo(j)} + (1-\rho_2)(1-\rho_1)\epsilon_{ij}. \tag{6}$$

This formulation follows the nested logit literature of Brenkers and Verboven (2006), which introduces the RCNL. First, utility shock ζ_{ig}^1 is common to all varieties within a same segment g of the industry.[17] Second, utility shock ζ_{igo}^2 is common to all varieties in the segment g imported from the same origin country o. 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_{ig}^1 and ζ_{igo}^2 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 $\rho_i \in [0,1]$, $i = 1, 2$, by governing the contribution of ζ_{ig}^1 and ζ_{io}^2 to the overall variance of utility shock $\bar{\epsilon}_{ij}$. For instance, varieties are equally substitutable between and within nests iff $\rho_1 = \rho_2 = 0$.

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

$$V_{ij} = \delta_j - \exp(\alpha_i) \ln p_j + \bar{\epsilon}_{ij}. \tag{7}$$

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 common utility δ_j of a foreign variety should be interpreted in deviation to the utility 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 μ_{ij} the 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_{ig}^1 and ζ_{igo}^2, we get a standard 2-level nested logit expression for the probability that i picks variety j:[20]

$$\mathbb{P}_{ij} = \mathbb{P}_i^{j|og} \times \mathbb{P}_i^{o|g} \times \mathbb{P}_i^{g} = \frac{\exp\left(\frac{\delta_j + \mu_{ij}}{1-\rho_1}\right)}{\exp\left(\frac{I_{iog}}{1-\rho_1}\right)} \times \frac{\exp\left(\frac{I_{iog}}{1-\rho_2}\right)}{\exp\left(\frac{I_{ig}}{1-\rho_2}\right)} \times \frac{\exp(I_{ig})}{\exp(I_i)} \tag{8}$$

[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.

[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 (2021) 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_{ig}^1 and ζ_{igo}^2 are such that $\zeta_{igo}^2 + (1-\rho_1)\epsilon_{ij}$ and $\bar{\epsilon}_{ij}$ are also distributed type-1 extreme value. See Cardell (1997) for a proof of the existence and uniqueness of such distributions for ζ_{ig}^1 and ζ_{igo}^2.

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

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

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

$$r_j = \int e(y_i)\mathbb{P}_{ij}\,di \tag{9}$$

where $e(y_i)$ is the total expenditures of consumer i and $\mathbb{P}_{ij}$ her 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

$$\alpha_i = \alpha + \pi\ln y_i + \sqrt{\sigma}\nu_i\,, \qquad y_i \sim F(y),\, \nu_i \sim G(\nu). \tag{10}$$

We assume that both $\ln y_i$ and ν_i have a normal distribution: while ν_i follows a standard normal, we allow for the mean and standard deviation of $\ln y_i$ to 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.

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

$$s_j \equiv \frac{r_j}{\sum_{j'\in\mathcal{J}} r_{j'}} = \int \mathbb{P}_{ij}\,\omega_i^{(Y)}di\,, \tag{11}$$

with $\omega_i^{(Y)} \equiv \frac{y_i}{\int y_i\,di}$ the share of consumer i 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 A 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

$$\ln c_j = \eta_j \lambda_j + h\lambda_j^2 + \rho x_j + \gamma_{g(j)} + \gamma_{f(j)} + \varphi_j. \tag{12}$$

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 $\gamma_{f(j)}$. Moreover, 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 simultaneously 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

$$\Pi_f(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{j \in \mathcal{J}_f} \pi_j(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{j \in \mathcal{J}_f} r_j(\boldsymbol{\lambda}, \boldsymbol{p}) \left(1 - \frac{c_j(\lambda_j)}{p_j}\right), \tag{13}$$

[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 C.

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

$$p_j^* = \left(1 - \frac{1}{\frac{\partial \ln r_j}{\partial \ln p_j}}\right) c_j = \left(1 + \frac{1}{\int \exp(\alpha_i)\, \mathcal{E}_{ij}\, \omega_{ij}^{(r)}\, di}\right) c_j\,, \tag{14}$$

with $\omega_{ij}^{(r)} \equiv \frac{\mathbb{P}_{ij} y_i}{\int \mathbb{P}_{ij}\, y_i\, di}$ the share of consumer i in the revenue of variety j (exponent "(r)" is a mnemonic for revenue) and $\mathcal{E}_{ij}$ the semi-elasticity of the purchasing probability $\mathbb{P}_{ij}$ with respect to the utility shifter δ_j:[24]

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

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 $\omega_{ij}^{(r)}$ 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 C 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

$$\lambda_j^* = \frac{1}{2h}\left(\tilde{\alpha}_j^{-1} - \eta_j\right) \qquad \text{with} \quad \tilde{\alpha}_j \equiv \int \exp(\alpha_i)\,\omega_{ij}^{(\mathcal{E})}\,di, \qquad \omega_{ij}^{(\mathcal{E})} \equiv \frac{\mathcal{E}_{ij}\,y_i\,\mathbb{P}_{ij}}{\int \mathcal{E}_{ij}\,y_i\,\mathbb{P}_{ij}di}. \tag{15}$$

$\tilde{\alpha}_j$ is a weighted average price elasticity of variety j's residual consumers. Introducing this variable in equation (15) 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 (15) 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 first, along with the set of instruments used to identify our demand system and the challenges associated with our data limitations. Finally, we conclude with the estimation of the cost of quality upgrading. Appendix A details the data construction.

4.1 Data Preparation

The footwear industry We estimate the model using data from the footwear industry,[25] motivated by two main 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 in France 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]

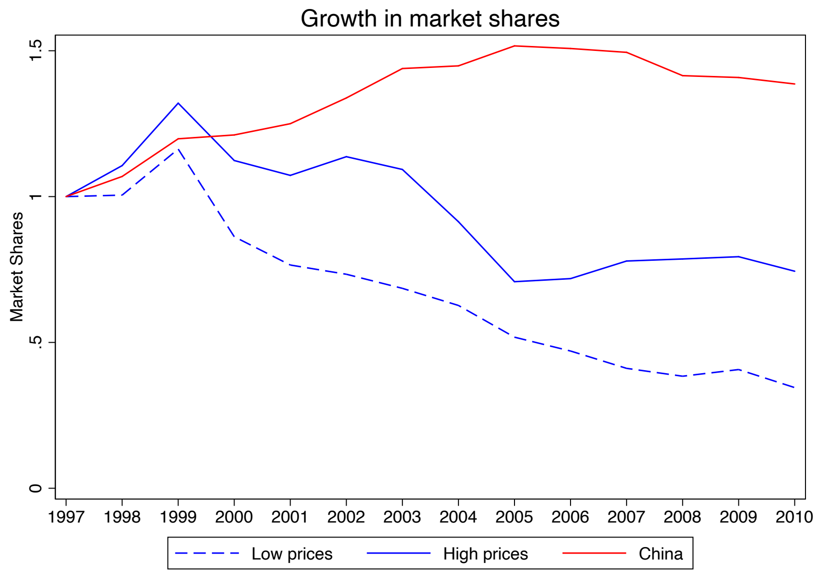

FIGURE 1: Chinese competition Hits Cheap Shoes Harder

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 in the distribution of shoe prices. In figure 2, we

[25] We focus on the HS6 product categories belonging to the HS2 category 64: 'Footwear; Gaiters and the like; parts of such articles', excluding HS6 categories starting with 6406 which are designed for various types of shoe parts.

[26] To construct figure 1, we divide French footwear varieties in quartiles based on their prices before 2001. For each of the three groups – Chinese varieties, cheap French varieties and expensive French varieties – we compute their market share on each HS6-destination-year market and we average them across markets every year, weighting each market by its initial number of French firms. We then report the evolution of the average market share for each group.

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.

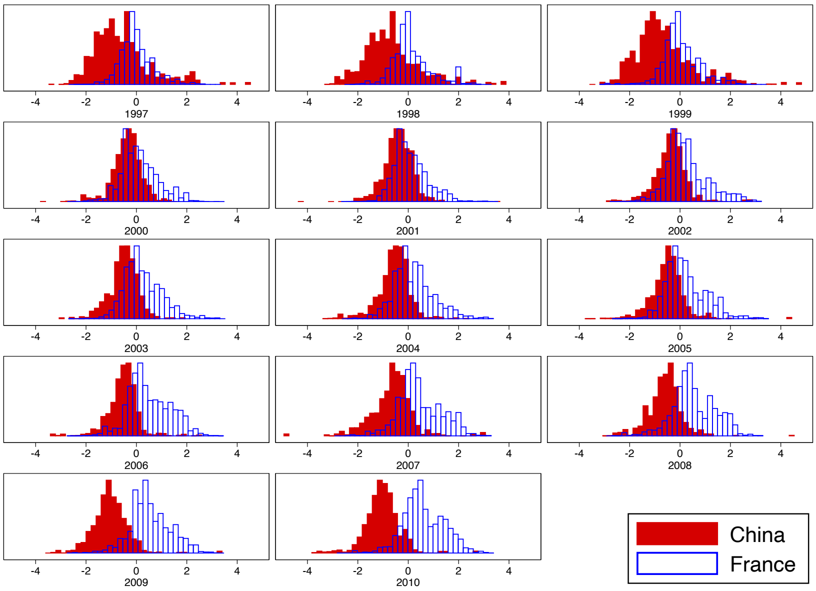

FIGURE 2: The price of French shoes diverges from Chinese competition

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, which can be a French firm or a foreign country. We use French customs data to obtain exported values and market shares of each French producer. Because firm-level data is not available from all other exporting countries, we use BACI to construct the market shares of other foreign countries for each variety and market.[28]

The estimation procedure also requires to construct the prices that consumers face in each destination market. Therefore, we inflate FOB unit values by an ad valorem transportation cost and tariffs rates. We compute transportation costs from the National Supply and Use Tables of 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

[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 A for details.

[28] We discuss the identification challenges created by this discrepancy between firm-level and country-level data in the next subsection.

'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. We obtain tariffs rates from the MacMap database that provides the bilateral applied tariffs at the HS6 level for the years 2001, 2004, 2007 and 2010.[29] As a result, we obtain import prices that account for transportation costs and tariffs duties, which reflect the final prices 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.[30] This cleaning procedure leaves us with 319 609 observations, including 145 422 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.[31] Note 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.[32] 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

[29]We extrapolate the data to obtain tariffs measures for all years from 1997 to 2010. See appendix A and Guimbard et al. (2012) for details.

[30]These different steps are described in A.

[31]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.

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

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:

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

and we construct the domestic prices from the first fixed effects $\hat{\gamma}_{ct}^{(1)}$ to obtain the price of the outside good at the country-year level. This method allows 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 Our demand system depends on 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

$$E\left[z_l\, \xi(\boldsymbol{\theta}_0)\right] = 0, \qquad \text{for} \quad l = 1, .., L \tag{16}$$

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. As made explicit by equation (10), the two primitive sources of heterogeneity across consumers are their income y and their random price-elasticity shock ν. From equation (11), we can therefore write the market share of a variety j in destination d at date t as an integral over (y, ν):

$$s_{jdt}(\boldsymbol{\delta}_{dt}, \boldsymbol{p}_{dt}; \boldsymbol{\theta}) = \int \mathbb{P}_{jdt}(y, \nu, \boldsymbol{\delta}_{dt}, \boldsymbol{p}_{dt}; \boldsymbol{\theta})\, \omega_d^{(Y)}(y)\, dy\, d\nu\,, \tag{17}$$

with $\omega_d^{(Y)}(y) \equiv \frac{yF_d(y)}{\int yF_d(y)\, dy}$ the share of consumers with income y in the national income of destination d. For each market dt, (17) 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 observable 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, and adapted to the presence of nests by Grigolon and Verboven (2014): from a given vector $\boldsymbol{\delta}^{(h)}$ at iteration h, we compute $\boldsymbol{s}(\boldsymbol{\delta}^{(h)}, \boldsymbol{p}; \boldsymbol{\theta})$ and iterate using

$$\boldsymbol{\delta}^{(h+1)} = \boldsymbol{\delta}^{(h)} + (1 - \max(\rho_1, \rho_2)) \cdot \left[\log \boldsymbol{S} - \log \boldsymbol{s}(\boldsymbol{\delta}^{(h)}, \boldsymbol{p}; \boldsymbol{\theta})\right], \tag{18}$$

until the minimum of the vector of squared difference between $\boldsymbol{\delta}^{(h+1)}$ and $\boldsymbol{\delta}^{(h)}$ is less than 10^{-12}.[33] We evaluate the integral in equation (17) by using a Gauss-Hermite product rule with 9^2 nodes, which ensures us to exactly integrate any polynomial of degree 17 or less.[34]

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

$$\delta_{jdt}(\boldsymbol{S}, \boldsymbol{p}; \boldsymbol{\theta}) = \beta x_{jdt} + \gamma_{g(j)} + \gamma_{f(j)} + \xi_{jdt}, \tag{19}$$

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.[35] 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 coefficients. 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.[36]

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

$$\hat{\boldsymbol{\theta}} = \text{argmin}_{\theta} \quad \hat{\xi}(\theta)' Z \Phi Z' \hat{\xi}(\theta) \tag{20}$$

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

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

[33] 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 (2020).

[34] This integration method is recommended by Conlon and Gortmaker (2020) in a context with a limited number of random coefficients.

[35] 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 (2021) for papers treating this bias.

[36] 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.

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 of equation (14) that accounts for the presence of multi-product firms.[37] 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, the supply-side of the model is not used to estimate the demand system. Instead, we recover marginal costs from the demand estimation, and subsequently 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 are costs shifters constructed from tariffs and exchange rates variations. 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. In our context, the use of international trade data allows us to use tariffs rates across countries as instruments for prices: tariffs directly affect the final price charged by a firm in foreign markets, while being unlikely to be correlated with demand shocks or quality decisions made by individual shoe producers.

Moreover, we also use exchange rates to construct a cost shifter that varies across French firms. We take advantage of the spatial structure of French imports to 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

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

[37] See equation (26) in appendix C.

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

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

In addition to these cost shifters, we also need instruments to identify the parameters ρ_1 and ρ_2 that measure the patterns of substitutions within and between nests. To identify these parameters, we follow the literature and use the number of competitors in the market, as well as the number of firms in the product category and product category × origin nests.[39] These instruments identify the nesting parameters by measuring what is the impact of an extra competitor on firms located in different nests. A stronger impact on firms located in the nest that the entrant just joined indicates stronger substitution patterns within nests than between, and identifies the relative degree of substitution measured by the parameters ρ. In order for these instruments to be valid, the numbers of firms in the different segments of the markets need to be uncorrelated with the demand shocks of individual producers. For instance, an increase in demand for a specific variety that would both attract new entrants and increase the demand for a given individual producer would be a threat to the identification. However, this concern is limited for two reasons. First, the literature emphasizes that the entry of new firms in export markets tends to be very sluggish. As such, it is unlikely that the entry of new firms responds rapidly to temporary demand shocks. Second, our estimation results will exhibit very strong substitution patterns within nests. If the entry of new firms was positively correlated with individual demand shocks, we would find a strong positive correlation in performance between firms operating in the same nest. Our estimation results show the opposite patterns, which is reassuring for the validity of the identification of these parameters.

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 IV": 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. To ensure the exogeneity of this measure, we construct it using predictions of prices, rather than prices themselves: we regress prices on the sets of exogenous characteristics and instruments, and use the predicted value to construct the differentiation IV. As a result, this instrument uses variations in tariffs and cost shifters to capture changes in the position of competitors in the price distribution and its impact on firms' performance. Moreover, we interact the two cost shifters above 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 two cost shifters (tariffs to destination and import-weighted exchange rates), three nested instruments (number of firms in the market, in the nest and in the sub-nest) and three differentiation IV (two cost shifters interacted with the income in the destination and number of firms in the market within one standard deviation of prices). Finally, we add two instruments by interacting the tariffs and the tariffs interacted with income,

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

with a dummy when the producer is a French firm. As we discuss in the next paragraph, this recognizes that the price elasticity of individual French firms might be different from the price elasticity of aggregate trade flows emanating from country-level data. As a result, our preferred specification has a total of ten instruments that identifies the six structural parameters of our model.[40]

Product-level data and hidden varieties The estimation of the demand system combines micro-level data for French exporters but also country-level data for varieties from other countries. This discrepancy between the use of trade flows at an aggregate level – HS6 $\times$ origin – for some producers and firm-level data for French producers presents two challenges.

First, it creates an issue for the consistency of our estimates. In the case of aggregate data at the country-HS6 level, the interpretation of the demand shifter as a measure of quality is not correct. 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 so-called "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 of the number of varieties exported. In other words, the price elasticity identified for foreign varieties will conflate the intensive margin (i.e. the change in exports for each firm in response to a price change) with the extensive margin (i.e. the increase in the number of exporters in response to lower prices).

In order to make sure that we estimate a firm-level price elasticity, we implement two alternative strategies. First, we allow the price of an exported variety to have a different impact for countries relative to firms. More precisely, we add an interaction between the price term and a dummy for non-French exports to capture differences in the average price elasticity at the firm level and at the country level. 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 non-French varieties 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 country-level trade flows have a larger response to cost shifters and, as a result, the price elasticity estimated on the sample of French firms is smaller.

The second challenge that aggregate data poses is to 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. It 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 Chinese prices and market shares.

In the absence of a dataset that combines disaggregated trade data from all countries, we assess the implications of this aggregation bias by simulating a sample that exhibits dispersion in prices within a country. Specifically, we disaggregate country-level trade flows into five dis-

[40] In appendix D, we show the robustness of our parameter estimates to changes in the set of instruments used in the estimation.

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

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

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.

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 (15), 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 (15). 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 $\frac{1}{2h}$, the 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 (12)) and the first order condition on quality leads to the following formulation of the marginal costs:

$$\ln c_{jdt} = x_{jt}\rho + \frac{1}{4h}\left(\tilde{\alpha}^{-1}_{jdt}\right)^2 - \frac{1}{4h}\eta^2_{jdt} + \varphi_{jdt}. \tag{21}$$

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 $\breve{\alpha}^{-1}$, which 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 $\breve{\alpha}^{-1}_{jdt}$, let us define $\boldsymbol{\delta}^{-j}_{dt}$ and $\boldsymbol{p}^{-j}_{dt}$ to be respectively the vector of utility shifters and prices of the competitors of variety j. $\breve{\alpha}^{-1}_{jdt}$ 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:

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

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

$$\begin{aligned}\breve{\alpha}^{-1}_{jdt} &= \frac{1}{\int \exp(\alpha_i)\breve{\omega}_{ijdt}\, di} \\ \text{with} \quad \breve{\omega}_{ijdt} &= \frac{\breve{\mathcal{E}}_{ijdt}\, y_i\, \breve{\mathbb{P}}_{ijdt}}{\int \breve{\mathcal{E}}_{ijdt}\, y_i\, \breve{\mathbb{P}}_{ijdt}\, di}.\end{aligned}$$

Similarly, $\breve{\mathcal{E}}_{ijdt}$ is an exogenous version of demand elasticity $\mathcal{E}_{ijdt}$, defined using the initial characteristics of variety j and the contemporaneous characteristics of its competitors.

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

We use $\breve{\alpha}^{-1}_{jdt}$ to estimate the relationship between quality and average price elasticity, equation (15), and between marginal cost and the square of the average price elasticity, equation (21). Because the variation of $\breve{\alpha}^{-1}_{jdt}$ 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 $\breve{\alpha}^{-1}_{jdt}$. 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

The results of the estimation are presented in table 5. In columns (1) and (2), we start by estimating a standard logit model to show the role of our instruments in the estimation of the price-elasticity. 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 leads to a change of sign in the price-elasticity. In the OLS specification, without instrumentation, we obtain a positive coefficient on prices. By contrast, the 2SLS specification (column 2) correctly leads to a negative price elasticity (-1.84). Moreover, the first stage F-statistic shows that our instruments are strong enough to correctly identify the price-elasticity in the second stage.

TABLE 5: Estimation results

	OLS	**2SLS**	**Nested Logit**		**RCNL**	
	(1)	(2)	(3)	(4)	(5)	(6)
log price	0.070	-1.84	-0.77	-0.93		
	(0.064)	(0.25)	(0.15)	(0.11)		
log price $\times$ *Country*			-1.05		-0.77	
			(0.22)		(0.25)	
log price $\times$ inc_d			0.96	0.34		
			(0.13)	(0.053)		
$\log s_{j\|og}$ (ρ_1)			0.91	0.77	0.78	0.73
			(0.051)	(0.018)	(0.072)	(0.022)
$\log s_{j\|g}$ (ρ_2)			0.40	0.34	0.24	0.30
			(0.11)	(0.031)	(0.14)	(0.039)
α					0.30	0.046
					(0.19)	(0.17)
π					-0.33	-0.22
					(0.06)	(0.091)
σ					0.00	0.00
					(0.20)	(0.11)
Average price elast.	0.070	-1.84	-2.95	-3.17	-5.63	-4.08
Sample	Full	Full	Full	French	Full	French
N	319 609	319 609	319 609	145 422	319 609	145 422
First stage F-stat		207.6	75.6	61.3		

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). For specifications (3) and (4), there is a total of 9 instruments: the cost shifters; the cost shifters interacted with the destination log average income; the number of firms in each level of nests (market, product group and product group-origin). 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). The average price elasticity reported are for French firms only, even when using the full sample.

In columns (3) and (4), we test for the presence of nests by estimating the double nested logit model. We include as regressors the share of a variety in its HS6 category and in its product category $\times$ origin groups to estimate the nesting parameters while maintaining the linearity of the model. We also 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. Consistent with the fact that consumers choose a product category first, and then an origin country, we find a larger coefficient within origin-product category nests (ρ_1) than within product categories (ρ_2). Moreover, we see that richer countries have a lower price elasticity, which suggests that income is a source of heterogeneity in preferences.[41] Finally, we confirm that country-level trade flows have a larger price elasticity than firm-level flows: the coefficient of -1.05 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 nested logit model using French firms only. The 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 model, respectively using the full sample and a sample with French firms only. The results confirm the importance of the nests in consumer 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 model. The value of these 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 0.30, which leads to a price elasticity of $-\frac{\exp(0.30)}{1-0.78} = -6.14$ for an atomistic firm in a destination with average income level. However, the average price elasticity across French firms is equal to 5.63, which reflects the fact that some 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 -0.33 means that a consumer with an income twice larger than the average consumer has a 30 percent lower price-elasticity. Regarding the impact of other sources of heterogeneity, we do not find a significant role for other shocks through the parameter σ, suggesting that 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.

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

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 accordingly. 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 (26), using parameter estimates from specification (5) in table 5 to parametrize the distribution of consumer preferences. The average markup among French varieties is around 20 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 10 percent markup, while others are closer to 60 percent.

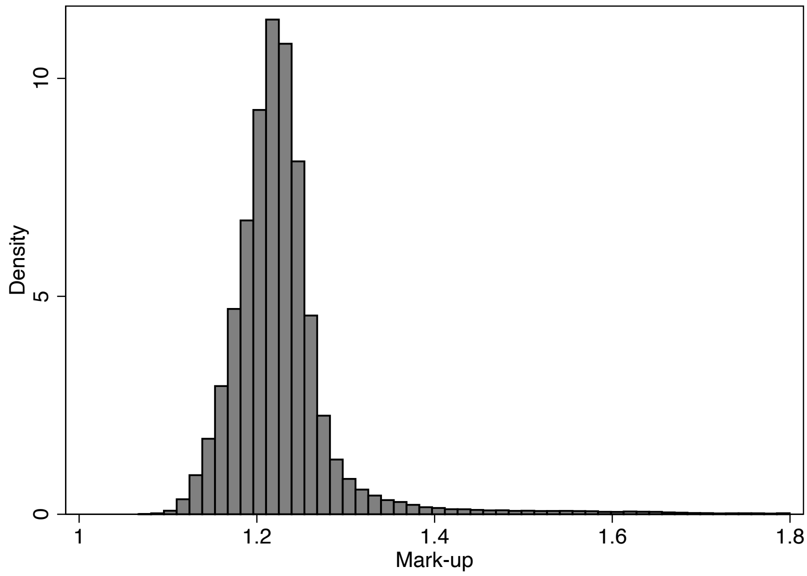

FIGURE 3: Distribution of markups of French firms

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).[42] 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 increases the markup charged by a firm by 0.04. Similarly, firms with higher

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

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.

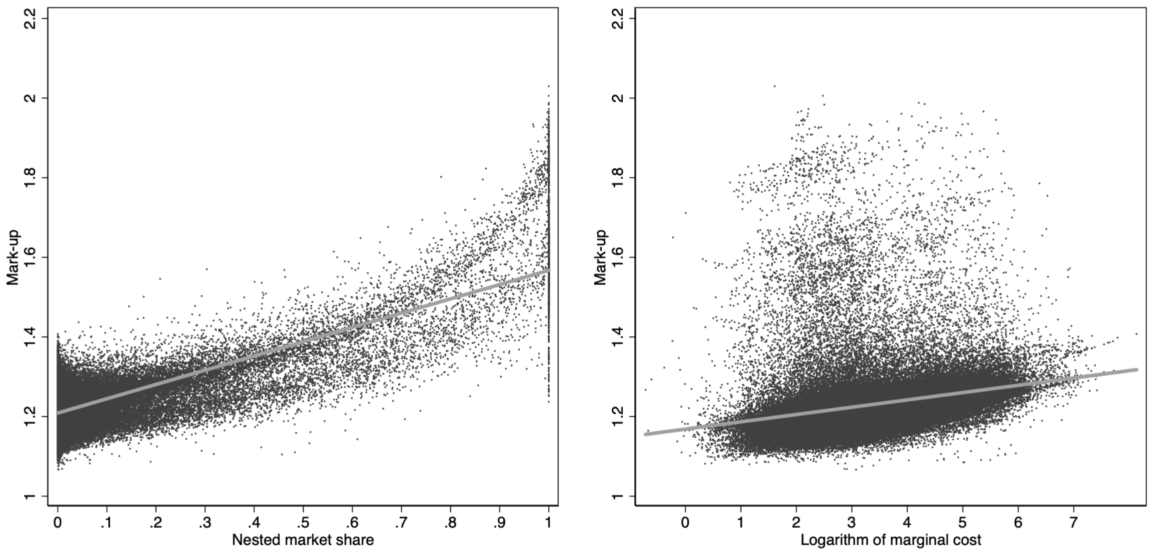

FIGURE 4: Correlation of markup with market share and quality

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 -10. This dispersion similarly reflects the fact that firms face very different average consumers, affecting their optimal response in terms of prices. The right panel of figure 5 shows that serving different consumers also implies that firms are unequally affected by low-cost competition. A large share of French firms are barely affected by Chinese prices, while some firms have a cross-price elasticity 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.

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

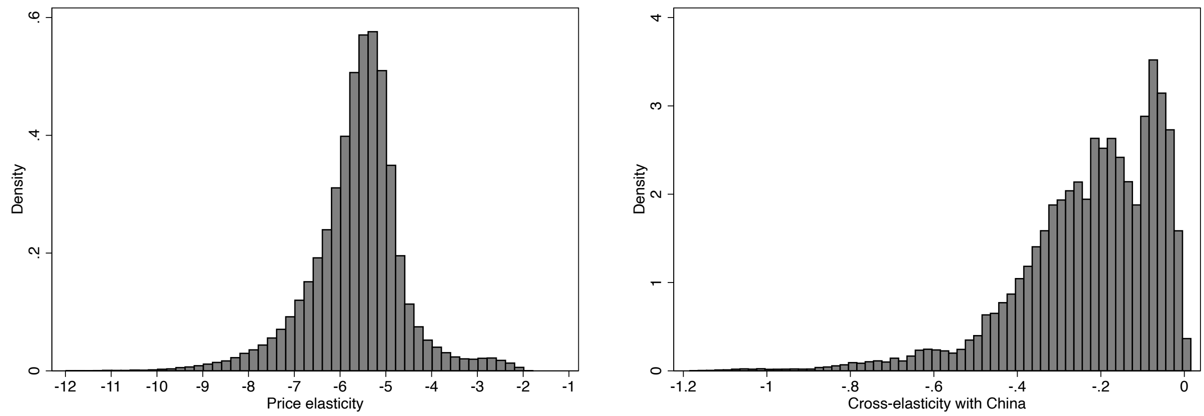

FIGURE 5: Distribution of own and cross-price elasticities (French firms).

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.[43]

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

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

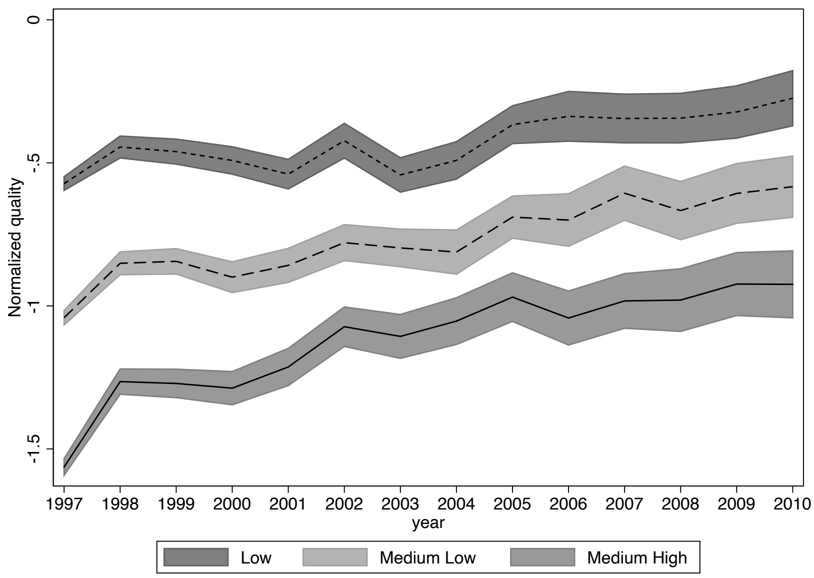

FIGURE 6: Low Price Varieties Upgrade their Quality over the Period

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

the 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 (15), 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 (21)).

We present the estimation results using both specifications in table 6. In all specifications, we use two sets of fixed effects. First, firm$\times$HS6$\times$destination fixed effects so that the identification comes from time variations in quality and marginal costs triggered by changes in competition.[44] Second, we include HS6$\times$destination$\times$year fixed effects so that we identify the impact between firms exporting to the same destination. 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) estimate the parameter $\frac{1}{4h}$.

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 7.95 and 3.33, which corresponds to a value for h around 0.07. 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.[45] With this exogenous variable, we obtain much smaller coefficients, respectively 2.59 and 1.63, which leads to a larger value for h. Since h mea-

[44] In table 14 in appendix D, we find very similar results using first differences and long differences instead of firm$\times$HS6$\times$destination fixed effects.

[45] Figure 10 in appendix D shows the scatterplots associated with these regressions.

Table 6: Estimation results: supply side

	(1)	(2)	(3)	(4)	(5)
	quality λ_{jdt}		$\log mc_{jdt}$		*Stacked*
$\tilde{\alpha}^{-1}$	7.95				
	(0.08)				
$\breve{\alpha}^{-1}$		2.59			
		(0.3)			
$(\tilde{\alpha}^{-1})^2$			3.33		
			(0.03)		
$(\breve{\alpha}^{-1})^2$				1.63	
				(0.1)	
$\breve{\alpha}^{-1}$ or $\frac{(\breve{\alpha}^{-1})^2}{2}$					2.93
					(0.3)
$\hat{h}$	0.063	**0.19**	0.075	**0.15**	**0.17**
N	123 528	123 528	123 528	123 528	247 056
R^2	0.98	0.94	0.99	0.88	0.99

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

sures 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 0.17, which is the value we use in the counterfactual experiment. In table 14 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. These specifications lead to a slightly higher estimate of h, but we show in figure 11 in appendix E that this higher value leads to qualitatively similar conclusions.

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

6 Quantifying the Unequal Impact of the China Shock

Having estimated a model of demand for the shoe industry, we can form predictions as to the performance of shoe producers in an alternative environment to the one actually observed in the data. In particular, we use the model to isolate the impact of the rise of China in the footwear market, and study its implications on French exporters. As we study the impact of Chinese competition, we are most interested in two elements. First, how heterogeneous is the effect of this shock along the price ladder. Second, to which extent has quality upgrading shielded French firms from the China shock.[46] 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

[46] 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.

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.[47] 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 the period. Yet, we see a lot of dispersion across products and categories: more than 25 percent of Chinese varieties lose market shares. This large number partly results from a reduction in the demand shifter of the losing products but is mostly explained by the increasing competition from other Chinese products. For instance, Chinese boots might lose market shares in Brazil because Chinese leather shoes gain so much in this destination market. Moving to French firms, almost all of them lose market shares as a result of the simulated China shock. The median French firm sees a 30 percent reduction in market shares, and we also find important heterogeneity among firms: 5 percent of those firms lose more than 90 percent of their market share, while 5 percent lose less than 2 percent.

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 ($s_{97}^{sim}/s_{97}^{actual} - 1$)

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 in deciles, based on their position in the local price distribution. For each decile, we compute the average change in market shares between the initial equilibrium and the simulated equilibrium (with post-2007 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 by the average loss in the top decile. As a result, we measure the additional loss in market share recorded by firms located in lower price deciles.

[47] Specifically, for each Chinese variety in each destination market, we compute the average price and demand shifter from 2008 to 2010.

Figure 7 reports the heterogeneous impact of Chinese competition across price deciles. In the left panel, we look at the heterogeneous 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 22 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.[48] In this model, we capture horizontal differentiation but rule out any role for vertical differentiation. We find that horizontal differentiation explains a bit more than half of the heterogeneous impact of competition, with the first decile having an additional 13 percentage points reduction in market shares on average.

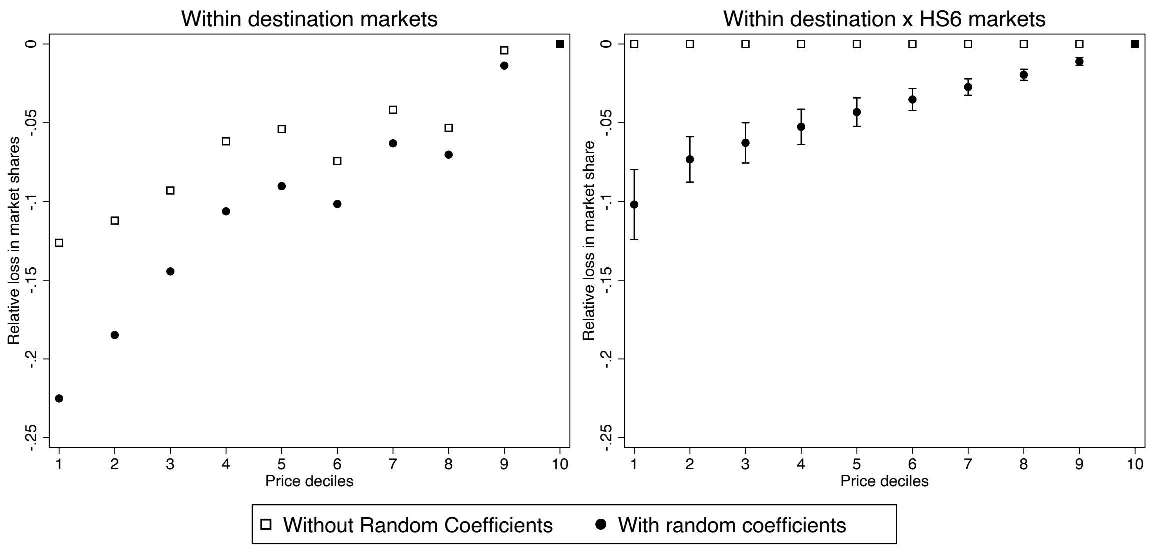

FIGURE 7: Effect of the China shock by price deciles (on French firms in 1997)

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).

To confirm the importance of vertical differentiation, the right panel of figure 7 looks at the impact of competition within destination$\times$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 10 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

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

moving along the price distribution directly affects firm 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 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.[49]

In order to solve for the new equilibrium, while taking into account the price and quality adjustments of French firms, we re-write the first order conditions to obtain an expression of firm counterfactual decisions as a function of their actual decisions. For any variable x, we define x' as its new equilibrium value after replacing Chinese fundamentals with their counterfactual values. Ignoring the market indices dt for clarity, we can rewrite the new equilibrium values:

$$\begin{cases} \lambda'_j & = \lambda_j + \frac{1}{2h}\left(\left(\tilde{\alpha}'_j\right)^{-1} - (\tilde{\alpha}_j)^{-1}\right) \\ \log c'_j & = \log c_j + \left(\tilde{\alpha}'_j\right)^{-1}\left(\lambda'_j - \lambda_j\right) + h\left(\lambda'_j - \lambda_j\right)^2 \\ m'_j & = 1 + \frac{1}{\int \exp(\alpha_i)\, \mathcal{E}'_{ij}\, \omega_{ij}^{(r)\prime}\, di} \\ \log p'_j & = \log m'_j + \log c'_j. \end{cases} \tag{22}$$

Because the set of supply side equations (22) is expressed relative to the existing equilibrium, we do not need to estimate idiosyncratic cost parameters – φ_{jdt} and η_{jdt} – to solve for the new equilibrium.[50] Beside actual firm decisions, evaluating (22) also requires counterfactual demand-

[49] 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.

[50] This result is similar to the exact hat algebra procedure introduced in Dekle, Eaton, and Kortum (2008) applied to the supply side. Note, however, that the presence of random coefficients in the demand system does not allow us to solve the counterfactual equilibrium without solving for the demand fundamentals. We show in appendix C 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 cost shifters.

side endogenous variables $\tilde{\alpha}'$, $\mathcal{E}'$ and $\omega^{(r)'}$, which verify

$$\begin{cases} \tilde{\alpha}'_j & \equiv \int \exp(\alpha_i)\, \omega^{(\mathcal{E})'}_{ij}\, di \\ \mathcal{E}'_{ij} & \equiv \frac{\partial \ln \mathbb{P}'_{ij}}{\partial \delta_j} \\ \omega^{(r)'}_{ij} & \equiv \frac{y_i\, \mathbb{P}'_{ij}}{\int y_i\, \mathbb{P}'_{ij} di} \end{cases} \quad \text{with} \quad \begin{cases} \omega^{(\mathcal{E})'}_{ij} & \equiv \frac{\mathcal{E}'_{ij}\, y_i\, \mathbb{P}'_{ij}}{\int \mathcal{E}'_{ij}\, y_i\, \mathbb{P}'_{ij} di} \\ \mathbb{P}'_{ij} & = \mathbb{P}_j(y_i, \nu_i, \boldsymbol{\lambda}', \boldsymbol{p}'; \boldsymbol{\theta}). \end{cases} \tag{23}$$

Starting from the actual firm decisions, we solve for the counterfactual equilibrium by alternatively updating demand-side variables through (23) and firm decisions through (22), until convergence is reached. 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 and compare these outcomes across price deciles within a destination-HS6 market, using the tenth decile as normalization. The dark bars on the figure report similar results to the previous subsection, with a rise in Chinese competition that generates an additional 10 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 0.7%: because Chinese firms have relatively low prices, French firms lose their most price-elastic customers to Chinese competitors and increase their price in response. Therefore, while the model accounts for oligopoly power and could predict a reduction in markup through a pro-competitive effect, the change in the price-elasticity of the average consumer served by French firms is the dominating force, leading to a rise in markup.[51] 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 0.2% 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 quality by 3% and figure 8 shows that firms in the bottom price decile increase their quality by an extra 1% relative to 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

[51]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.

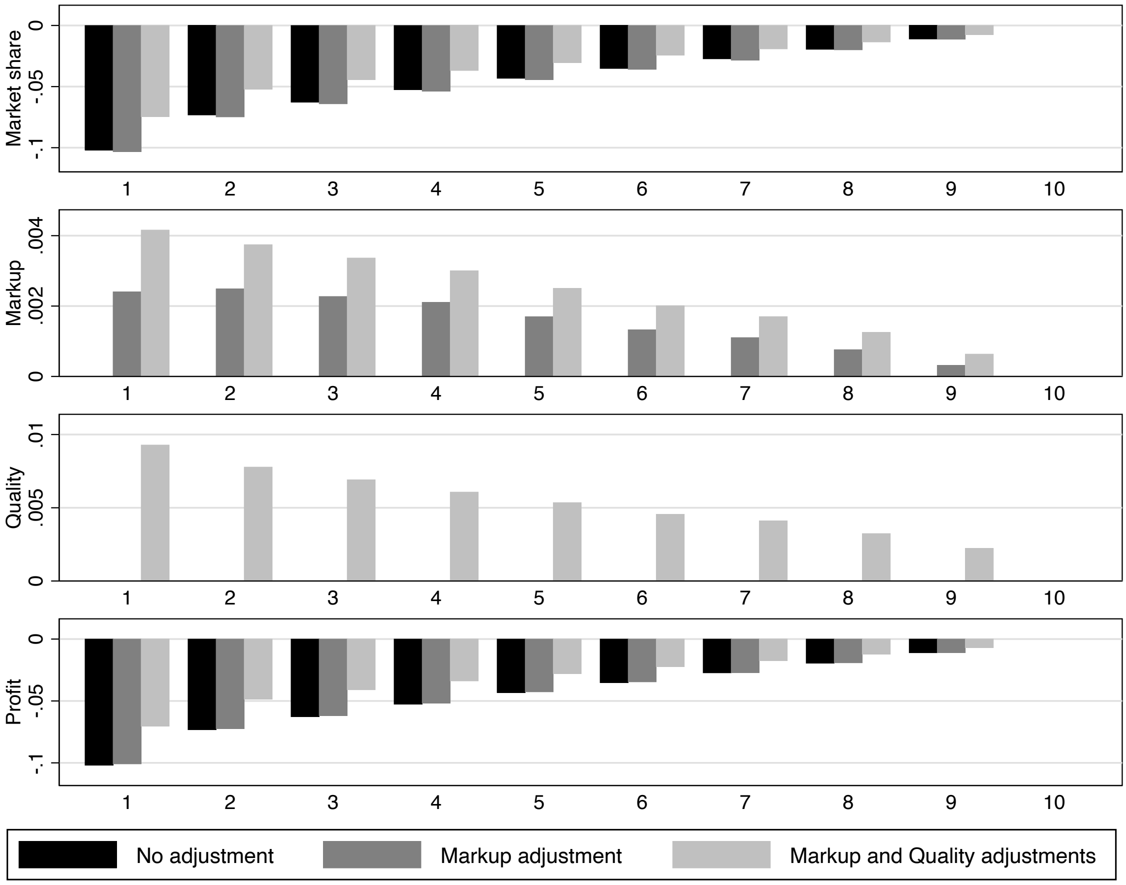

FIGURE 8: Effect of the China shock and the quality response

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.

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 record an extra 10% reduction in market share relative to the top decile, this gap is reduced to 7% when firms adjust their quality. Overall, quality upgrading can reduce one third of the unequal impact of Chinese competition.

In conclusion, these results highlight an important quality response. Quality upgrading helps mitigate some of the additional impact that low-price firms face due to higher exposure to Chinese competition. Nevertheless, the cost of quality upgrading is large enough that high-price firms still suffer significantly smaller losses.

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 10 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 heterogeneous 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.

References

Adao, R., A. Costinot, and D. Donaldson (2017): "Nonparametric counterfactual predictions in neoclassical models of international trade," *The American Economic Review*, 107, 633–689.

Ahn, J., H. Han, and Y. Huang (2017): "Trade with Benefits: New Insights on Competition and Innovation," *Manuscript*.

Almunia, M., P. Antras, D. Lopez-Rodriguez, and E. Morales (2021): "Venting Out: Exports during a Domestic Slump," *American Economic Review*, 111, 3611–62.

Amiti, M. and A. K. Khandelwal (2013): "Import competition and quality upgrading," *Review of Economics and Statistics*, 95, 476–490.

Anderson, S. P., A. De Palma, and J.-F. Thisse (1992): *Discrete choice theory of product differentiation*, MIT press.

Autor, D. H., D. Dorn, and G. H. Hanson (2013): "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 103, 2121–2168.

Autor, D. H., D. Dorn, G. H. Hanson, and J. Song (2014): "Trade Adjustment: Worker-Level Evidence," *The Quarterly Journal of Economics*, 129, 1799–1860.

Bas, M. and V. Strauss-Kahn (2015): "Input-trade liberalization, export prices and quality upgrading," *Journal of International Economics*, 95, 250–262.

Bastos, P., J. Silva, and E. Verhoogen (2018): "Export destinations and input prices," *American Economic Review*, 108, 353–92.

Bellone, F., P. Musso, L. Nesta, and F. Warzynski (2014): "International trade and firm-level markups when location and quality matter," *Journal of Economic Geography*, 16, 67–91.

Bernard, A. B., E. A. Boler, R. Massari, J.-D. Reyes, and D. Taglioni (2017): "Exporter dynamics and partial-year effects," *American Economic Review*, 107, 3211–28.

Bernard, A. B., J. B. Jensen, and P. K. Schott (2006): "Survival of the Best Fit: Exposure to Low-wage Countries and the (uneven) Growth of US Manufacturing Plants," *Journal of International Economics*, 68, 219–237.

Berry, S., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, 63, 841–90.

Bloom, N., M. Draca, and J. Van Reenen (2016): "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," *Review of Economic Studies*, 83, 87–117.

Brenkers, R. and F. Verboven (2006): "Liberalizing a distribution system: the European car market," *Journal of the European Economic Association*, 4, 216–251.

Cardell, N. S. (1997): "Variance components structures for the extreme-value and logistic distributions with application to models of heterogeneity," *Econometric Theory*, 13, 185–213.

Conlon, C. and J. Gortmaker (2020): "Best practices for differentiated products demand estimation with pyblp," *The RAND Journal of Economics*, 51, 1108–1161.

Coşar, A. K., P. L. Grieco, S. Li, and F. Tintelnot (2018): "What drives home market advantage?" *Journal of international economics*, 110, 135–150.

Dekle, R., J. Eaton, and S. Kortum (2008): "Global rebalancing with gravity: Measuring the burden of adjustment," *IMF Staff Papers*, 55, 511–540.

Dubé, J.-P., A. Hortaçsu, and J. Joo (2021): "Random-coefficients logit demand estimation with zero-valued market shares," *Marketing Science*.

Eaton, J., S. Kortum, and F. Kramarz (2011): "An Anatomy of International Trade: Evidence from French Firms," *Econometrica*, 79, 1453–1498.

Edmond, C., V. Midrigan, and D. Y. Xu (2015): "Competition, markups, and the gains from international trade," *American Economic Review*, 105, 3183–3221.

Faber, B. and T. Fally (2021): "Firm Heterogeneity in Consumption Baskets: Evidence from Home and Store Scanner Data," *The Review of Economic Studies*.

Fajgelbaum, P., G. Grossman, and E. Helpman (2011): "Income Distribution, Product Quality, and International Trade," *Journal of Political Economy*, 119, 721–765.

Fajgelbaum, P. D. and A. K. Khandelwal (2016): "Measuring the unequal gains from trade," *The Quarterly Journal of Economics*, 131, 1113–1180.

Feenstra, R. C. and J. Romalis (2014): "International prices and endogenous quality," *The Quarterly Journal of Economics*, 129, 477–527.

Fieler, A. C., M. Eslava, and D. Y. Xu (2018): "Trade, quality upgrading, and input linkages: Theory and evidence from colombia," *American Economic Review*, 108, 109–46.

GANDHI, A. AND J.-F. HOUDE (2017): "Measuring substitution patterns in differentiated products industries," *Manuscript.*

GANDHI, A., Z. LU, AND X. SHI (2020): "Estimating demand for differentiated products with zeroes in market share data," *Available at SSRN 3503565.*

GAULIER, G. AND S. ZIGNAGO (2010): "BACI: International Trade Database at the Product-Level (the 1994-2007 Version)," *Manuscript.*

GOLDBERG, P. K. (1995): "Product differentiation and oligopoly in international markets: The case of the US automobile industry," *Econometrica: Journal of the Econometric Society*, 891–951.

GOLDBERG, P. K. AND F. VERBOVEN (2001): "The evolution of price dispersion in the European car market," *The Review of Economic Studies*, 68, 811–848.

GRIGOLON, L. AND F. VERBOVEN (2014): "Nested logit or random coefficients logit? A comparison of alternative discrete choice models of product differentiation," *Review of Economics and Statistics*, 96, 916–935.

GUIMBARD, H., S. JEAN, M. MIMOUNI, AND X. PICHOT (2012): "MAcMap-HS6 2007, an exhaustive and consistent measure of applied protection in 2007," Working Papers 2012-10, CEPII.

HALLAK, J. AND P. SCHOTT (2011): "Estimating Cross-Country Differences in Product Quality," *Quarterly Journal of Economics*, 126, 417–474.

HEAD, K., T. MAYER, ET AL. (2021): *Poor Substitutes?: Counterfactual Methods in IO and Trade Compared*, Centre for Economic Policy Research.

HEINS, G. (2021): "Endogenous Vertical Differentiation, Variety, and the Unequal Gains from Trade," *The Review of Economics and Statistics*, 1–45.

HOLMES, T. AND J. STEVENS (2014): "An Alternative Theory of the Plant Size Distribution, with Geography and Intra-and International Trade," *Journal of Political Economy*, 122, 369–421.

HOTTMAN, C., S. J. REDDING, AND D. E. WEINSTEIN (2016): "Quantifying the Sources of Firm Heterogeneity," *Quarterly Journal of Economics.*

HOTTMAN, C. J. AND R. MONARCH (2020): "A matter of taste: Estimating import price inflation across U.S. income groups," *Journal of International Economics*, 127.

KHANDELWAL, A. (2010): "The Long and Short (of) Quality Ladders," *Review of Economic Studies*, 77, 1450–1476.

KUGLER, M. AND E. VERHOOGEN (2012): "Prices, Plant Size, and Product Quality," *Review of Economic Studies*, 79, 307–339.

MARTIN, J. AND I. MEJEAN (2014): "Low-wage Country Competition and the Quality Content of High-wage Country Exports," *Journal of International Economics*, 93, 140 – 152.

MEDINA, P. (2020): "Import Competition, Quality Upgrading and Exporting: Evidence from the Peruvian Apparel Industry," *University of Toronto mimeo.*

NEWEY, W. K. AND D. MCFADDEN (1994): "Large sample estimation and hypothesis testing," *Handbook of econometrics*, 4, 2111–2245.

Pierce, J. R. and P. K. Schott (2012): "Concording US Harmonized System Codes over Time," *Journal of Official Statistics*, 28, 53–68.

Piveteau, P. (2021): "An Empirical Dynamic Model of Trade with Consumer Accumulation," *American Economic Journal: Microeconomics*, 13, 23–63.

Piveteau, P. and G. Smagghue (2019): "Estimating firm product quality using trade data," *Journal of International Economics*, 118, 217 – 232.

Roberts, M., D. Xu, X. Fan, and S. Zhang (2017): "The role of firm factors in demand, cost, and export market selection for chinese footwear producers," *The Review of Economic Studies*, 85, 2429–2461.

Semykina, A. and J. M. Wooldridge (2010): "Estimating panel data models in the presence of endogeneity and selection," *Journal of Econometrics*, 157, 375–380.

Van Beveren, I., A. B. Bernard, and H. Vandenbussche (2012): "Concording EU Trade and Production Data over Time," Working Paper 18604, National Bureau of Economic Research.

Varadhan, R. and C. Roland (2004): "Squared extrapolation methods (SQUAREM): A new class of simple and efficient numerical schemes for accelerating the convergence of the EM algorithm," .

Verhoogen, E. (2008): "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector," *Quarterly Journal of Economics*, 123, 489–530.

Appendices

A Data Appendix

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

Geographical Coverage We limit the set of source and destination countries to the 40 countries present in the WIOD database. For countries absent from WIOD, we are unable to implement the estimation as we cannot construct variables such as CIF prices or the market share of the outside good. Moreover, we also exclude France from the set of destination countries because we 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 (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,[52] 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 refer to 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

[52] 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.

cost. These transportations costs are computed from the National Supply and Use Tables, which are part of WIOD. These data contain bilateral free-on-board (FOB) value and transportation costs at the 2-digit level of the Statistical classification of products by activity (CPA) from 1995 to 2011. We compute the ad valorem transportation cost at the importing country, exporting country, CPA level by taking the average over the period of the ratio between transportation costs and FOB trade.

Tariffs data Our tariff measures come from the Market Access Map (MAcMap) dataset provided by the CEPII. It provides bilateral information on the applied tariffs rates at the HS6 level for four years: 2001, 2004, 2007 and 2010. We use 2001 values for the years 1997 to 2001 and use linear interpolation for years from 2001 to 2010. Because Romania and Bulgaria do not provide import tariffs data for 2004, we use data from 2001 instead for these two countries.

Data Cleaning Information on prices in trade data is known to be noisy. In order to mitigate this issue, we identify prices with extreme values in the data and correct them. In the case of firm-level data, we remove firms with extreme values from the dataset. However, in the case of country-level data, we correct these values as follows.

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.

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 domestic 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. Since we observe this price for many destinations, we infer the domestic unit values by regressing the logarithm of the FOB unit value on a set of fixed effects:

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

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

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

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

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

B Motivating Evidence Appendix

The Heterogeneous Impact of China In our motivating evidence (section 2), we document the heterogeneous impact of competition from low-cost countries. In this paragraph we show that our results are robust to limiting our analysis to Chinese competition.

Tables 9 and 10 report the heterogeneous impact of Chinese competition along the price distribution of French exporters. Similarly to tables 1 and 3, we look at the intensive, the extensive and the price margin and we report both the OLS and IV estimates. The main picture remains: Chinese competition, just like low-cost competition in general, hurts low-price varieties relatively more than high-price varieties, both at the intensive and extensive margins.

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

Dependent variable:	*log export*		*Exp. participation*	
Estimator:	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Chinese penetration				
× 2nd price quartile	0.22***	0.33*	0.025***	0.032*
	(0.068)	(0.19)	(0.0076)	(0.019)
× 3rd price quartile	0.29***	0.54***	0.045***	0.10***
	(0.067)	(0.18)	(0.0085)	(0.022)
× 4th price quartile	0.21***	0.50**	0.077***	0.20***
	(0.082)	(0.24)	(0.0097)	(0.027)
N	6 303 097	6 180 629	13 806 800	13 612 039
First stage F-stat		95.7		159.8

Notes: Standard errors clustered at the HS6+ level, between parentheses. All specifications include product-destination-year and firm-product-destination fixed effects. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 10 also shows similar results when looking at the price response to Chinese competition: low-price French firms, which are hurt relatively more from Chinese competition, also sees a stronger increase in their prices in response to this competition.

Table 10: Price responses to Chinese competition

Dependent variable:	*log price*	
Estimator:	OLS	2SLS
	(1)	(2)
Chinese penetration		
× 2nd price quartile	-0.64***	-1.74***
	(0.050)	(0.13)
× 3rd price quartile	-1.00***	-2.98***
	(0.057)	(0.17)
× 4th price quartile	-1.71***	-4.81***
	(0.097)	(0.28)
N	6 303 097	6 180 629
First stage F-stat		95.7

Notes: Standard errors clustered at the HS6+ level, between parentheses. All specifications include product-destination-year and firm-product-destination fixed effects. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

Positioning of French prices relative to Foreign Competition Our hypothesis to explain the stronger impact of low-cost competition on low-cost French exporters is that varieties that are closer in the product space (and in particular in the price distribution) display stronger substitution patterns. Figure 9 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.

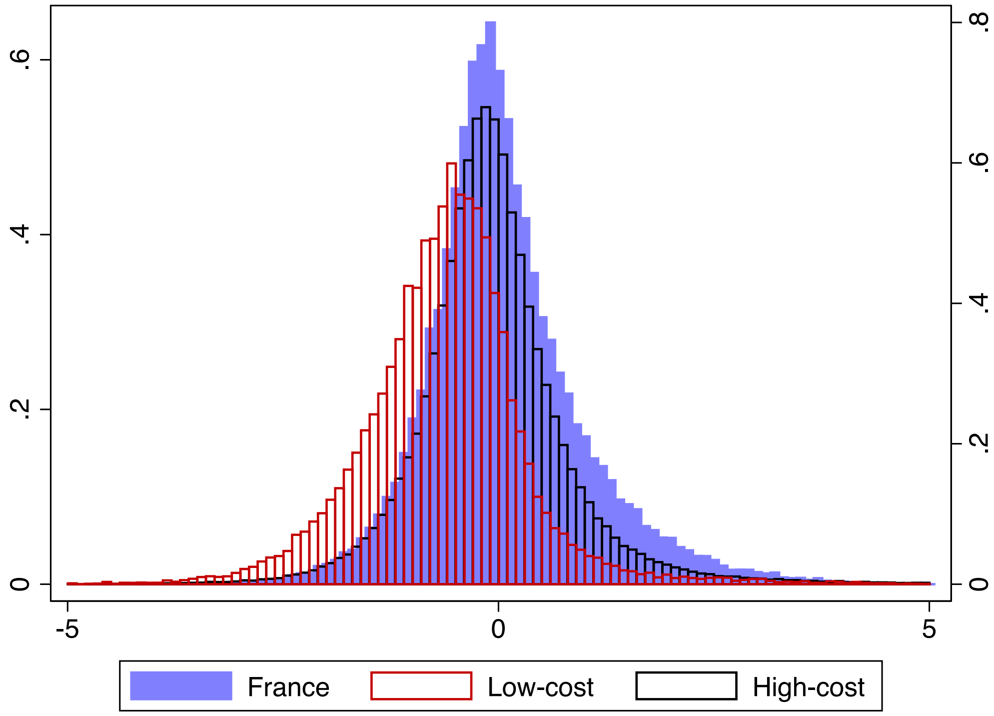

FIGURE 9: Distribution of Export prices

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.

Interdependence across Markets and the Impact of Low-cost Competition Firm decisions have been shown to be interdependent across destination/product markets, due for instance to the presence of increasing marginal costs (see Almunia et al. (2021)). In principle, it could be that such interdependence drive the fact that low-price firms suffer more from low cost-competition. For instance, it would be the case if low-price firms reallocate more of their exports away from exposed markets than high-price firms. If anything, we would expect the opposite given that low-price firms are likely to produce other low-quality products, and therefore to experience similar trajectories, across products and markets.

In order to verify this intuition, we construct measures of interdependence at the firm level. The idea of interdependence is that the export flow of a firm f to a destination d in 6-digit product category p may be impacted by demand shocks happening in other destinations $d' \neq d$ or other products $p' \neq p$, in which the firm is also active. We rely on a shift-share approach to build a proxy for firm-level demand shocks on other markets. Our measure of demand shocks faced by firm f at date t on products other than p is

$$D_{ft}^{(-p)} = \sum_{p' \neq p} \omega_{fp'}^{(-p)} D_{p't},$$

where $D_{pt} \equiv \sum_{f,d} export_{fpdt}$ are total French exports of product p in year t and $\omega_{fp'}^{(-p)}$ is the share of product p' in the global sales of firm f over 1997-2000, *excluding product* p:

$$\omega_{fp'}^{(-p)} = \frac{\sum_{t=1997}^{2000} \sum_d export_{fp'dt}}{\sum_{p'' \neq p} \sum_{t=1997}^{2000} \sum_d export_{fp''dt}}.$$

In practice, within a destination-product $p \times d$, $D_{ft}^{(-p)}$ will grow faster for firms specializing in products whose global sales grow faster. Similarly, we build $D_{ft}^{(-d)} \equiv \sum_{d' \neq d} \omega_{fd'}^{(-d)} D_{d't}$ as the demand shock faced by firm f at date t on other destinations than d. Within a destination-product d, $D_{ft}^{(-d)}$ will grow faster for firms serving destinations whose total imports from France grow faster.

Table 11 reports the estimated impact of low-cost competition on French firms along the price distribution. In column (2) and (4) we include $\ln D_{ft}^{(-d)}$ and $\ln D_{ft}^{(-p)}$ to control for interdependencies across destinations and products. The results show that these controls do not modify the heterogeneous impact of low-cost competition across price quartiles. We do find that the coefficients on $\ln D_{ft}^{(-d)}$ and $\ln D_{ft}^{(-p)}$ are significant in some specifications: it suggests that there is some substitution in export values across destination markets, consistent with Almunia et al. (2021), and complementarity in export entry across markets and products.

In conclusion, interdependencies across markets cannot explain the heterogeneous impact of low-cost competition. This points to a demand-side mechanism, which motivates the estimation of a more realistic demand system.

Table 11: High-price varieties suffer less from low-cost competition

Dependent variable:	*log export*		*Selection*	
Estimator:	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Low-cost penetration				
× 2nd price quartile	0.32**	0.31**	0.057***	0.057***
	(0.15)	(0.15)	(0.017)	(0.017)
× 3rd price quartile	0.39**	0.38**	0.13***	0.13***
	(0.16)	(0.16)	(0.019)	(0.019)
× 4th price quartile	0.12	0.11	0.22***	0.22***
	(0.20)	(0.20)	(0.023)	(0.022)
Interdependence:				
across destinations ($\ln D_{ft}^{(-d)}$)		-0.073***		0.031***
		(0.02)		(0.004)
across products ($\ln D_{ft}^{(-p)}$)		0.023		0.017***
		(0.015)		(0.003)
N	6 268 551	6 261 486	13 747 041	13 732 406
First stage F-stat	477.7	478.2	602.7	603.0

Notes: Standard errors clustered at the HS6+ level, between parentheses. All specifications include product-destination-year and firm-product-destination fixed effects. Significance levels: * p<0.05, ** p<0.01, *** p<0.001.

C Theory Appendix

In this appendix, we start by deriving the derivatives of the purchasing probability with respect to the common utility shifter δ. Then, we detail the optimality conditions in the case of multi-product firms. 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

$$\mathbb{P}_{ij} = \mathbb{P}_i^{j|og} \times \mathbb{P}_i^{o|g} \times \mathbb{P}_i^{g} = \frac{\exp\left(\frac{\delta_j+\mu_{ij}}{1-\rho_1}\right)}{\exp\left(\frac{I_{iog}}{1-\rho_1}\right)} \times \frac{\exp\left(\frac{I_{iog}}{1-\rho_2}\right)}{\exp\left(\frac{I_{ig}}{1-\rho_2}\right)} \times \frac{\exp(I_{ig})}{\exp(I_i)} \tag{24}$$

with

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

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

$$\Pi_f(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{k \in \mathcal{J}_f} \pi_k(\boldsymbol{\lambda}, \boldsymbol{p}) = \sum_{k \in \mathcal{J}_f} r_k(\boldsymbol{\lambda}, \boldsymbol{p}) \cdot \left(1 - \frac{c_k(\lambda_k)}{p_k}\right), \tag{25}$$

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:

$$\boldsymbol{M} - \boldsymbol{\Delta}(1 - \boldsymbol{M}) = 0\,, \tag{26}$$

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

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

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

$$\begin{aligned}
\frac{\partial r_k}{\partial \ln p_j}\frac{1}{r_j} &= \frac{\partial}{\partial \ln p_j}\left(\int \mathbb{P}_{ik} y_i \, di\right)\frac{1}{r_j} \\
&= \frac{\int \frac{\partial \mathbb{P}_{ik}}{\partial \ln p_j}\, y_i}{\int \mathbb{P}_{ij}\, y_i \, di} \\
&= -\frac{\int \exp(\alpha_i)\frac{\partial \ln \mathbb{P}_{ik}}{\partial \delta_j}\, \mathbb{P}_{ik}\, y_i \, di}{\int \mathbb{P}_{ij} y_i \, di} \\
&= -\int \exp(\alpha_i)\mathcal{E}_{ikj}\, \omega^{(r)}_{ikj} di,
\end{aligned}$$

with $\omega^{(r)}_{ikj} \equiv \frac{\mathbb{P}_{ik}\, y_i}{\int \mathbb{P}_{ij}\, y_i \, di}$ the sales of variety k to consumer i relative to the total sales of variety j.

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:

$$\frac{p_j}{c_j} = 1 + \frac{1}{\Delta_{jj}} = 1 + \frac{1}{\int \exp(\alpha_i)\, \mathcal{E}_{ij}\, \omega^{(r)}_{ij}\, di}\,.$$

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

$$
\begin{aligned}
-\frac{\partial r_k}{\partial \lambda_j}\frac{1}{r_j} &= -\frac{\partial}{\partial \lambda_j}\left(\int \mathbb{P}_{ik}\, y_i di\right)\frac{1}{r_j} \\
&= -\frac{\int \frac{\partial \mathbb{P}_{ik}}{\partial \lambda_j}\, y_i di}{\int \mathbb{P}_{ij}\, y_i\, di} \\
&= -\frac{\int \frac{\partial \ln \mathbb{P}_{ik}}{\partial \delta_j}\, \mathbb{P}_{ik}\, y_i\, di}{\int \mathbb{P}_{ij}\, y_i di} \\
&= -\int \mathcal{E}_{ikj}\, \omega_{ikj}^{(r)}\, di,
\end{aligned}
$$

Given our specification of the marginal costs of production in equation (12), 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

$$
\lambda_j^* = \frac{1}{2h}\left(\tilde{\alpha}_j^{-1} - \eta_j\right) \quad \text{with} \quad \tilde{\alpha}_j = \frac{\Delta_{jj}}{G_{jj}} = \frac{\int \exp(\alpha_i)\mathcal{E}_{ij}\, \omega_{ij}^{(r)}\, di}{\int \mathcal{E}_{ij}\, \omega_{ij}^{(r)}\, di} = \int \exp(\alpha_i)\, \omega_{ij}^{(\mathcal{E})}\, di
$$

and $\omega_{ij}^{(\mathcal{E})} = \frac{\mathcal{E}_{ij}\, \omega_{ij}^{(r)}}{\int \mathcal{E}_{ij}\, \omega_{ij}^{(r)}\, di}$.

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 (15) is

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

so that we can obtain the counterfactual optimal quality λ'_{jdt} from the actual λ_{jdt} as follows:

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

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

Similarly, the marginal cost function (12) is defined as

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

so that we can write

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

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

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

which is the relationship we use to update the marginal cost from the initial equilibrium.

D Estimation Appendix

Entry, Exit and the Patterns of Substitution In order to get a sense of the importance of selection in our results, we implement a Heckman two-step approach to estimate the nested logit version of the model. Controlling for selection in the full model would be much more challenging, while it can be achieved easily for the nested logit, due to its linear specification. This allows us to get a sense of whether the estimates of price-elasticity, the nesting structure and the role of income drastically change when controlling for selection.

To implement this correction, we first need to estimate the probability of exporting: we expand the dataset by creating export dummies for all years and estimate a probit model using all instruments as regressors. From this prediction, we construct the inverse mills ratio for each observation and use it as additional regressor in the main specification. This additional term is used to test for the presence of endogenous selection, but also to control for the bias generated by this selection on other parameters.

The implementation of the Heckman correction in our context involves two additional requirements. First, the specification contains producer-level fixed effects that cannot be estimated in the probit model that aims at explaining export participation. To circumvent this issue, we follow Semykina and Wooldridge (2010) and use the so-called Mundlak method to control for producer-level unobserved heterogeneity: for each firm or country, we compute the average values of each regressor and add them as additional variables in the probit specification when estimating the probability of exporting. Second, the standard errors need to account for the variability introduced by the first stage of the estimation. Therefore, we obtain valid standard errors through bootstrap. Specifically, we use 100 bootstrap samples that are clustered at the producer level and use firms and countries as different strata to maintain the specific structure of our data; we measure standard errors from the standard deviations of these 100 estimates.

We present the results that account for selection in table 12. We report the baseline result – without accounting for selection – in column (1) for the full sample and in column (3) for the sample restricted to French firms. Columns (2) and (4) report the results when accounting for endogenous selection through the inclusion of the inverse Mills ratio. The first observation from this table is that there appears to be some selection in the data: the inverse Mills ratio is significant when using the full sample, and while insignificant due to large standard errors in the French sample, the Mills ratio remains economically important. Despite the existence of endogenous selection, we find limited impact on the parameter estimates, with the exception of the average price elasticity. We do find that the price elasticity is larger for the full sample when we account for selection, but these differences might be due to very large standard errors on this parameter. Regarding the parameters that drive the substitution patterns – $log\, price \times income$, ρ_1 and ρ_2 – we find little differences once we account for selection. This suggests that while we could underestimate the price elasticity by not accounting for selection, the patterns of substitution are relatively similar across specifications.

We find these results reassuring regarding the potential bias that endogenous selection could create in the full model.

Table 12: Estimation results controlling for selection

	(1)	(2)	(3)	(4)
log price	-0.77***	-1.77**	-0.93***	-1.03
	(0.15)	[0.87]	(0.11)	[0.84]
log price $\times$ *Country*	-1.05***	-1.27**		
	(0.22)	[0.50]		
log price $\times$ inc_d	0.96***	1.08***	0.34***	0.37***
	(0.13)	[0.26]	(0.053)	[0.11]
$\log s_{j\|og}$ (ρ_1)	0.91***	0.64***	0.77***	0.65***
	(0.051)	[0.17]	(0.018)	[0.10]
$\log s_{j\|g}$ (ρ_2)	0.40***	0.20	0.34***	0.40**
	(0.11)	[0.19]	(0.031)	[0.19]
Mills ratio		2.15**		0.97
		[0.90]		[0.98]
Sample	Full	Full	French	French
N	319 609	319 609	145 422	145 422
First stage F-stat	75.6	26.5	61.3	61.4

Notes: Standard errors between parentheses clustered at the producer level. Standard errors between brackets are based on 100 bootstrap samples 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 cost shifters, their interaction with the destination log average income, the number of firms in each level of nests (market, product group and product group-origin) and the number of competitors in the market located within one standard deviation in the price distribution (total of 10 instruments). The Mills ratio is constructed from a logit model that includes all instruments, hs6 fixed effects and producer-level averages of each variable.

Sensitivity to the set of Instruments The estimation of the model uses 10 instrumental variables to identify the 6 non-linear parameters of the model. As a result, we have enough instruments to investigate the stability of the estimates across different instrument sets. To study this stability, we identify 6 "core instruments" that directly map into the identification of the 6 parameters of the model. These instruments are:

- the log of tariff to identify the average price-elasticity,
- the log of tariff interacted with the income in the destination to identify the role of income on the price-elasticity,
- the log of tariff interacted with being a country as producer to identify the larger trade elasticity due to the extensive margin and the presence of hidden varieties,
- the number of firms in the product nest to identify the substitution within product category,
- the number of firms in the product-origin nest to identify the substitution within product-origin,
- the number of firms within one standard deviation in prices to identify the random coefficients on prices.

Having identified this core set of instruments, we test the sensitivity of our estimates when changing the set of instruments employed. We start with these 6 instruments (just-identified case) and add each additional instrument separately. Finally, we compare these results with the full specifications and the 10 instruments. In table 13, we report the baseline specification in column (1), the just-identified case with 6 instruments in column (2) and the results when adding separately each parameter in columns (3)-(6).

TABLE 13: Robustness to the set of instruments

	(1)	(2)	(3)	(4)	(5)	(6)
ρ_1	0.78	0.80	0.79	0.84	0.80	0.77
	(0.072)	(0.080)	(0.080)	(0.081)	(0.079)	(0.083)
ρ_2	0.24	0.26	0.25	0.28	0.26	0.24
	(0.14)	(0.18)	(0.15)	(0.18)	(0.18)	(0.19)
α	0.30	0.61	0.25	0.75	0.58	0.72
	(0.19)	(0.44)	(0.21)	(0.24)	(0.41)	(0.42)
π	-0.33	-0.35	-0.36	-0.35	-0.36	-0.33
	(0.062)	(0.35)	(0.066)	(0.15)	(0.35)	(0.32)
σ	0.00	0.00	0.00	0.00	0.00	0.00
	(0.20)	(0.14)	(0.24)	(0.11)	(0.15)	(0.13)
$\log price \times$ Country	-0.77	-0.53	-1.00	-0.27	-0.57	-0.26
	(0.25)	(0.28)	(0.23)	(0.23)	(0.28)	(0.31)
Number of instru.	10	6	7	7	7	7
Core instruments	✓	✓	✓	✓	✓	✓
$\log \tau \times Inc_d \times French$	✓		✓			
Number of firms	✓			✓		
Imported ex. rate	✓				✓	
Imported ex. rate $\times Inc_d$	✓					✓

Notes: N= 319 607. 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. Each specification contains a different set of instruments. The core instruments are the log tariff, its interaction with a country dummy and the income in the destination Inc_d, the numbers of producers in a hs6 and hs6-origin nests, and the number of producers within a standard deviations of predicted prices (6 instruments). From this set of core instruments that just identifies the model's parameters, we add individual instruments in specifications (3), (4), (5) and (6).

The results across the different sets of instruments show the relative stability of the estimation. In particular, we find remarkably stable coefficients related to the degree of substitution across varieties: both the nesting parameters (ρ_1 and ρ_2) and the random coefficients (π and σ) have highly similar estimates across sets of instruments. There is a more variation in the estimates of the price-elasticities (α and the parameter on $\log p\times$ Country) but this mostly reflects the large standard errors on these parameters when we use a smaller number of instruments.

Supply side estimation In this paragraph, we present additional results related to supply side estimation to account for adjustment frictions in the short run. First, in table 14 we report estimates of h – the cost of quality upgrading – obtained from first-difference and long difference regressions. These specifications lead to a slightly higher estimate of h, compared to fixed effects specification (6). However, we show in figure 11 (appendix E) that this higher value leads to qualitatively similar conclusions.

TABLE 14: Estimation results: supply side (using differences)

	$\Delta\lambda_{jdt}$			$\Delta \log mc_{jdt}$			*Stacked*		
$\Delta\tilde{\alpha}^{-1}$	2.20	2.07	2.03						
	(0.3)	(0.4)	(0.6)						
$\Delta(\tilde{\alpha}^{-1})^2$				1.15	1.04	1.10			
				(0.1)	(0.2)	(0.2)			
$\Delta\breve{\alpha}^{-1}$ or $\Delta\frac{(\breve{\alpha}^{-1})^2}{2}$							2.25	2.08	2.11
							(0.2)	(0.4)	(0.5)
Diff. length	1 y.	3 y.	5 y.	1 y.	3 y.	5 y.	1 y.	3 y.	5 y.
$\hat{h}$	0.23	0.24	0.25	0.22	0.24	0.23	0.22	0.24	0.24
N	82 255	38 103	19 523	82 255	38 103	19 523	164 510	76 206	39 046
R^2	0.31	0.37	0.40	0.075	0.098	0.13	0.25	0.30	0.32

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

Second, figure 10 display the scatterplot associated to the regressions from table 6 which estimate parameter h.

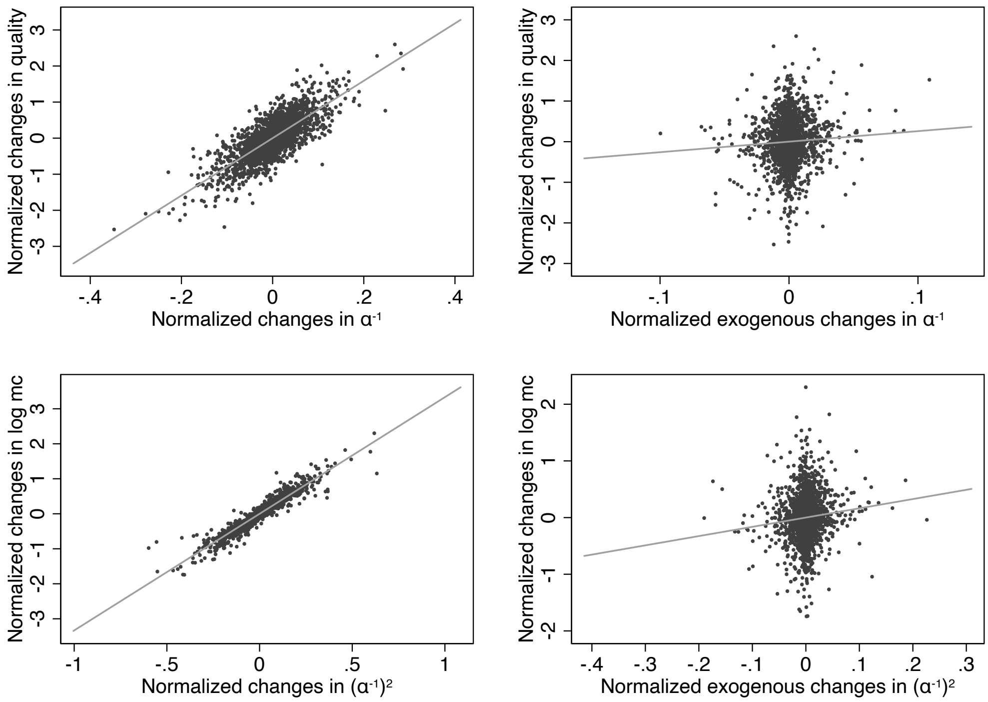

FIGURE 10: Estimation of the convexity of the marginal cost function

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.

E Counterfactuals

In this appendix, we investigate the sensitivity of our counterfactual results.

Sensitivity to the Cost of Quality Upgrading – h To this end, we replicate figure 8 using a larger value of h to calibrate the simulation ($h = 0.25$ instead of $h = 0.17$). The main conclusion remains : (i) among French footwear exporters, low-cost producers suffer more from the China shock than high-price producers and (ii) quality upgrading offers an imperfect protection against Chinese competition. Quantitatively, a larger value of h strengthens conclusion (ii). Specifically, with $h = 0.25$ quality upgrading reduces the market share losses of low-cost producers by about 25% (as opposed to 33% with $h = 0.17$).

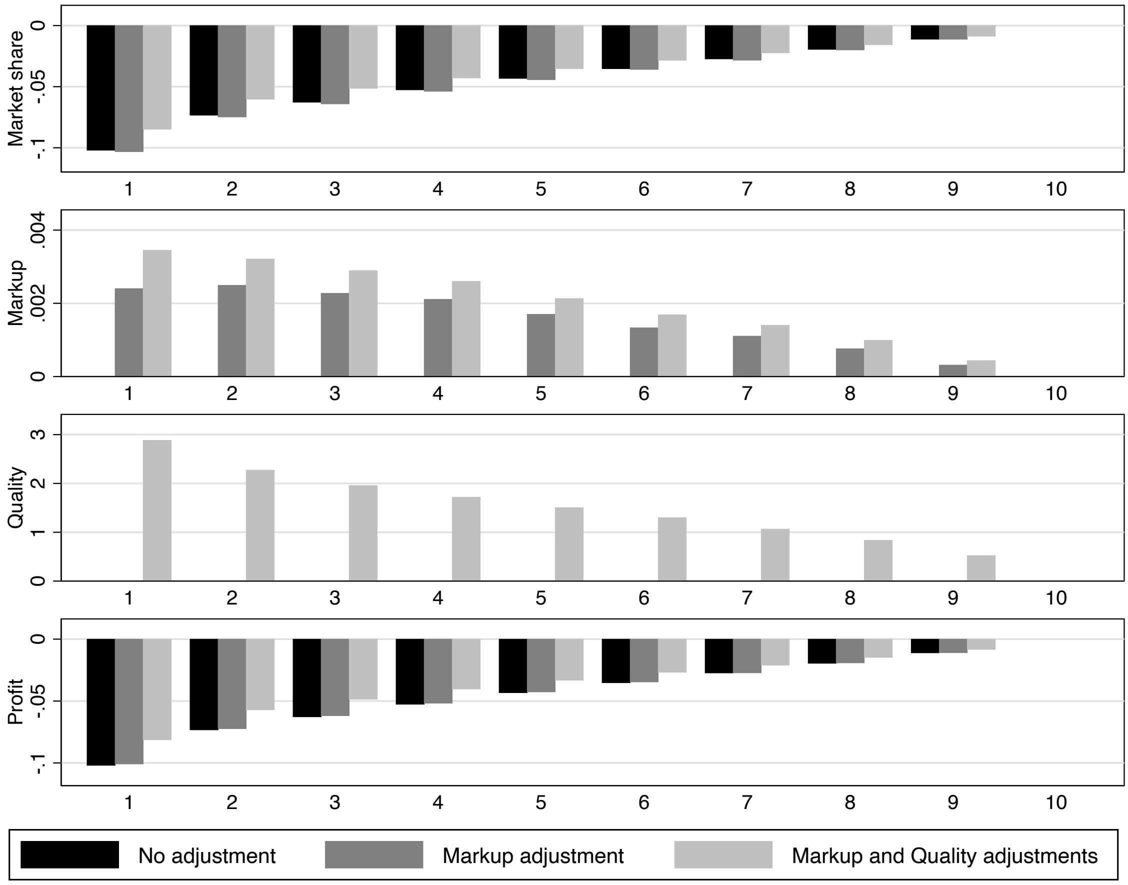

FIGURE 11: Counterfactual experiment: robustness with $delta = 0.25$

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. This figure is similar to figure 8 except for the use of $\delta = 0.25$ in the construction of the counterfactual experiment.

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.[53] 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 12 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.

[53]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.

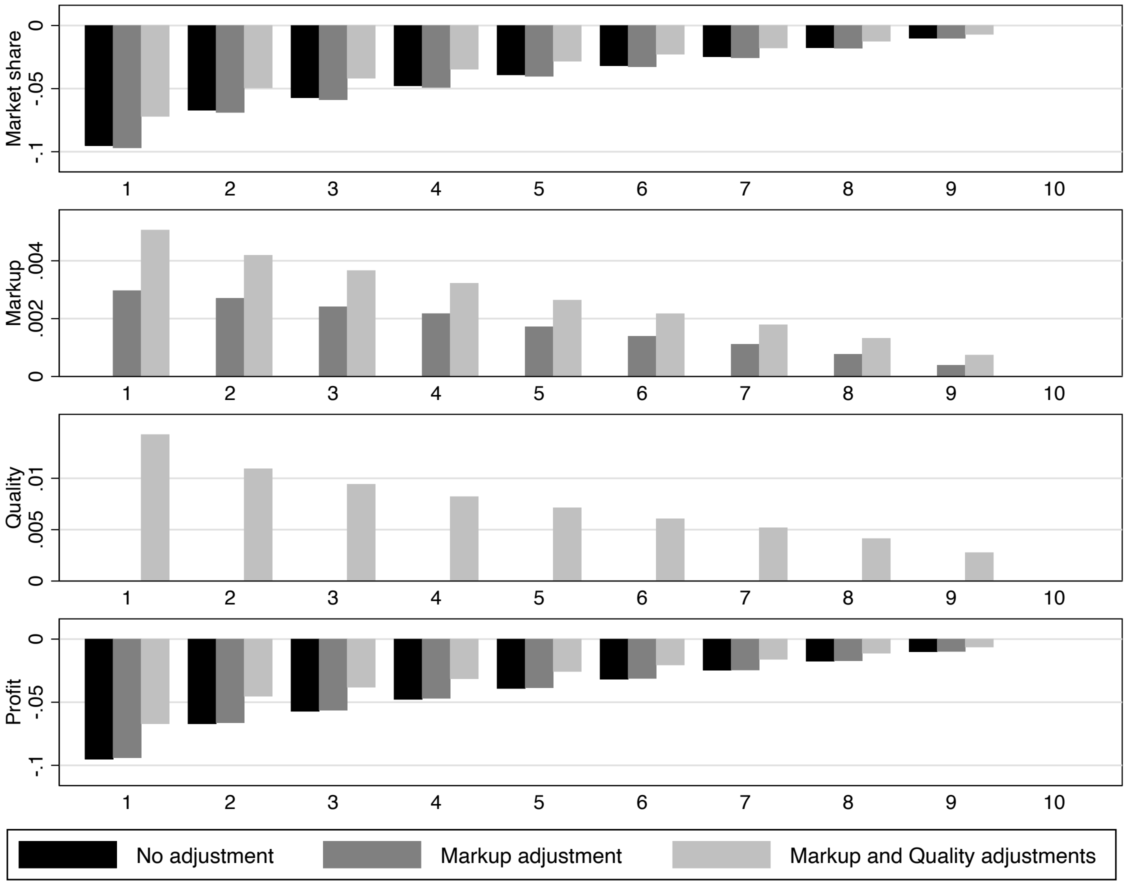

FIGURE 12: Effect of the China shock (disaggregated data)

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.