Inside the White Box: Unpacking the Determinants of Quality and Vertical Specialization*

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Abstract

This paper explores patterns of quality differentiation and specialization relying on model-level panel data of retail sales and prices of refrigerators across 23 countries in the European Union. Unlike customs data aggregated at the product category, typically used in the trade literature, model-level data allow us to test for the presence of nonhomotheticicities by comparing market shares of identical models across different markets. We measure quality at the model level, account for varying willingness-to-pay for quality at different incomes, and link quality measures to objective model attributes. Using originally assembled data on the country of manufacture of each model, we study patterns of quality specialization by brands with plants in multiple countries. We find that firms locate the production of their higher-quality models in richer countries and argue that the home-market effect linked to nonhomothetic preferences is a key driver of such patterns of quality specialization.

JEL Classification: F1; F14

Keywords: Inferred quality; Nonhomothetic CES; Home-market effect; Quality Specialization

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1 Introduction

Product specialization along the quality dimension has become one of the key subject matters in international trade. A cornerstone of this strand of the literature is the stylized fact that richer economies tend to be both exporters and importers of higher quality varieties of products. This finding has led to new perspectives on international product cycles and on the intensity of trade flows between countries at different stages of development, shifting the traditional Ricardo-Viner focus on inter-industry trade towards vertical differentiation and intra-industry trade. A growing consensus in the quality specialization literature is that the income-quality nexus reflects, to a large extent, the impact of rising demand for quality at higher income levels. This mechanism, which generates a 'home-market effect,' implies that local demand profiles become a crucial driver of international specialization patterns.

The relationship between the home market effect and quality specialization hinges on two related questions: Are preferences for quality nonhomothetic? If so, how does the impact of nonhomothetic demand compare to traditional supply-side mechanisms in driving quality specialization? Providing accurate answers to these questions is key to guiding theoretical models that study the evolution of trade flows and product localization in vertically differentiated industries. Furthermore, the proper design of policies aimed at influencing specialization patterns depends crucially on whether these patterns respond mainly to local factor endowments or demand conditions.

This paper offers new insights to the international trade literature on quality specialization by exploiting features of a detailed dataset that follows sales of identical models of refrigerators across 23 EU countries. By looking at market shares of identical models across different markets, and assembling a novel dataset pinpointing the location of the plant of production, we can analyze whether the geographic configuration of quality specialization within brands responds to nonhomothetic demand patterns, generating a home-market effect. The focus on a specific industry like refrigerators is crucial, as it exhibits several essential features instrumental to this paper's purpose. First, it represents an industry with a considerable degree of quality differentiation across models. Second, the leading producers in this industry are large multi-product international brands with several plants spread out in different countries. Third, in many cases, these international brands have plants in countries/regions that exhibit substantial levels of income disparity.

Empirically assessing the main drivers of international quality specialization poses a first challenge in finding an accurate method for measuring quality. Since Khandelwal (2010), inferring quality from consumer choices has become the standard approach in the empirical international trade literature.[1] Yet, the contributions following this approach have typically not taken into account that nonhomotheticities alter preferences for quality at different levels of income, and thus the sets of purchased varieties tend to vary with income. The main reason for this is to do with data limitations: quality measures have generally been inferred from customs data that aggregate sales within product categories. As a result, comparisons across countries (and time) may confound the impact of income variation on market shares for a given individual commodity with differences in the composition of (time-varying) commodity bundles.[2]

In this paper, we rely on model-level panel data on prices and unit sales of refrigerators traded in the European Union. We supplement the data with originally assembled information on products' country of manufacture (origin). Based on this augmented data set, we: i) test for the presence of nonhomotheticities along the quality dimension; ii) extend Khandelwal's (2010) approach to estimate quality measures that account for nonhomothetic demand; iii) contrast those measures against objective product attributes; iv) assess the role of local demand profiles on quality specialization by multinational firms.

The use of model-level data yields several methodological refinements. First, it allows us to move past the within-product-category aggregation issue and thus estimate model-specific quality measures, which are not vulnerable to bundle-composition bias in the presence of nonhomotheticities. Second, it permits a decomposition analysis of the quality estimates based on demand residuals by evaluating the extent to which product attributes explain the estimated quality. Third, it enables incorporating a rich set of fixed effects, including product indicators, to ensure that the estimation accounts for all time-invariant unobservable product characteristics possibly correlated with market shares.[3] Lastly, using the information on models' country of manufacture, we address price endogeneity by exploiting bilateral exchange rate movements as an instrumental variable.

We make three main contributions to the literature. The first contribution is specific to

[1] This method superseded an earlier approach relying on unit values as a proxy of product quality, e.g., Schott (2004), Hummels and Klenow (2005), Hallak (2006).

[2] One distinction that can be made in this literature is between papers relying on country-product-destination level data (e.g., Amiti and Khandelwal, 2013; Crino and Ogliari, 2017; Berlingieri, Breinlich and Dhingra, 2018; Heins, 2020), and those making use of firm-product-destination level data (e.g., Khandelwal, Schott and Wei, 2013; Martin and Mejean, 2014; Piveteau and Smagghue, 2019, 2020; Lashkaripour, 2020). Regardless of whether they exploit country-level or firm-level data, these papers rely on cross-country variation of bundles of imports/exports within narrowly defined product categories.

[3] While the literature using Khandelwal's (2010) approach also tends to exploit the panel dimension of customs data by including product fixed effects, these do not capture the same variation as our product-level fixed effects. Their product fixed effects control for the average effect of time-varying bundles of varieties within each product category. As a result, composition changes over time may lead to a correlation between the deviations from the (average) quality of the variety mix and deviations from the (average) price of the variety mix at different points in time.

the literature that envisions product quality as a demand shifter (e.g., Khandelwal, 2010). We apply this methodology to our data set and link inferred quality measures to a number of vertical attributes.[4] The estimates show that attributes most clearly associated with vertical differentiation among refrigerators can explain a significant amount of variability in quality across models (between 60% and 70%). Besides its own relevance, these results can be deemed the first systematic attempt to assess the validity of quality measures implicitly obtained as demand shifters from residuals against a large set of attributes that can be vertically ranked.[5]

The second contribution is testing for the presence of nonhomothetic preferences along the quality dimension by exploiting the variation of market shares of identical models across EU markets. To this end, we use nonhomothetic CES preferences as in Matsuyama (2019) and adapt them to a context of vertically differentiated varieties.[6] An advantage of these preferences is that they embed the standard homothetic CES utility as a special case. As a result, we can obtain quality measures within a framework that assumes as valid the homothetic CES case, and test for its validity within the more general nonhomothetic CES utility. Our results show that higher-quality fridge models command proportionally larger market shares in richer economies, thus lending support to the notion that preferences are non-homothetic. This result is especially noteworthy as it is rarely the case that market shares for *identical* models have been systematically compared across different countries with different levels of income.[7]

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[4]Linking consumer choices to observed product characteristics has also been central in the discrete-choice-model with random coefficients literature in Industrial Organization (e.g., Berry, 1994; Berry, Levinsohn and Pakes, 1995; Petrin, 2002).

[5]By linking inferred quality measures to objective fridge attributes, our paper relates to several recent articles that use objective measures of quality. Crozet, Head and Mayer (2012) and Chen and Juvenal (2016) rely on experts' assessments to study how quality can account for differences in export values and prices among, respectively, French champagne and Argentine wine producers. Sheu (2014) uses product-level data on attributes of printers imported in India to assess the impact of three sources of welfare gains following trade liberalization: changes in price, quality upgrading, and increasing variety. Auer, Chaney and Saure (2018) rely on hedonic price theory applied to several model-specific attributes to create quality categories for European cars. Our paper differs from those articles in that it adheres to an approach that infers product quality from consumer choices and, more importantly, our findings allow us to link quality measures to supply-side patterns of quality specialization.

[6]Similar preferences have been used also by Comin et al. (2021), and their general properties have been intially studied by Hanoch (1975) as part of the class of implicitly additively separable preferences.

[7]Previous evidence of nonhomothetic behavior along the quality dimension has relied chiefly on unit values as a proxy of quality (e.g., Schott, 2004; Hallak, 2006; Verhoogen, 2008; Bastos and Silva, 2010; Manova and Zhang, 2012). Feenstra and Romalis (2014) refine this approach by modeling supply-side heterogeneity, which allows them to decompose unit values into quality and quality-adjusted prices. Three exceptions to relying on unit values are Handbury (2021), Piveteau and Smagghue (2020) and Heins (2020) based on log-logit demand structures. Handbury (2021) studies the presence of nonhomothetic demand patterns along the quality dimension in the case of groceries consumption across US cities, and how income-specific tastes matter when computing cost of living in different geographic locations. Piveteau and Smagghue (2020) and Heins (2020) accommodate nonhomothetic demand schedules by allowing price elasticities of certain goods to decrease with consumer income.

This paper's third and main contribution pertains to production location patterns of multinational firms in a context of an industry with a large scope for vertical differentiation. By merging the panel data on sales with information on models' country of origin, we link quality estimates and production location choices. The resulting dataset enables us to assess patterns of vertical specialization at different levels of income per head. We show that richer economies tend to produce higher quality products, and demand-side aspects are important drivers of this association. The results thereby provide direct evidence supporting the relevance of the home-market effect, initially proposed by Linder (1961) and formalized in Fajgelbaum, Grossman and Helpman (2011), as a mechanism leading to specialization along the quality dimension across different economies. Furthermore, we show that production location decisions along the quality dimension do not seem to respond as strongly to differences in local factor endowments. These findings add to the evidence in Dingel (2017) based on micro-data on manufacturing plants across U.S. cities, who argues that local income plays a quantitatively more prominent role in explaining quality specialization across U.S. cities than differences in factor abundance.[8]

Exploring variation within brands with plants located in different countries leads to new insights. We show that the patterns of quality differentiation by income of country of manufacture are analogously replicated within brands. This finding suggests that the home market effect driving quality differentiation across countries is strong enough to operate even *within* firms, leading them to geographically split production across plants in different countries to exploit comparative advantage along the quality dimension. To the best of our knowledge, this is the first study to empirically demonstrate the comparative advantage of wealthier economies in higher quality versions of goods at such a granular level of production units. Importantly, we structure the analysis within a framework that can accommodate the use of both homothetic and nonhomothetic preferences, thus circumventing well-known drawbacks of proxying quality with unit values stemming from, for example, variations in input costs or pricing-to-market (see, e.g., Simonovska (2015)).

Our findings offer some general normative insights for trade policy that call attention to demand-side factors as key determinants of specialization. Trade policies aiming at promoting exports to developed economies have traditionally focused on enhancing supply-side factors, such as skills upgrading, investment in infrastructure, and improving financial markets (see, e.g., Verhoogen, 2008; Brambilla, Lederman and Porto, 2012;

[8] Our results tying nonhomothetic preferences along the quality dimension and the presence of a home-market effect as a major determinant of vertical specialization may also provide a rationale for the strong degree of consumer home bias found in two case studies involving the automobile industry by Goldberg and Verboven (2001) and by Cosar, Grieco, Li and Tintelnot (2018). In particular, our analysis may help interpret the consumer home bias as resulting (at least partially) from the presence of a home market effect where the quality of production is better customized to local (income-dependent) demand profiles.

Manova, 2013; Fieler, Eslava and Xu, 2018). The impact of nonhomothetic preferences on quality specialization via a home-market effect means that demand-side conditions should not be overlooked. The gravity force of the home-market effect implies that geographic proximity to richer consumers or, alternatively, strengthening trade links with richer importers need to be considered as additional necessary conditions for climbing up the quality ladder of production.

The paper proceeds as follows. Section 2 describes the main dataset. Section 3 infers quality measures at the model level, under the special case of homothetic CES utility, and links those measures to models' objective attributes. Section 4 introduces the more general demand-side framework with nonhomothetic CES utility and tests for the presence of nonhomotheticicities. Section 5 studies patterns of quality specialization by firms, showing that nonhomothetic preferences lead to a home-market effect that constitutes a driving force behind specialization patterns. Section 6 concludes.

2 Data and Summary Statistics

Our empirical analysis uses three separate sources of data. Our main dataset is a panel of cold appliances (refrigerators) provided by Gesellschaft für Konsumforschung (GfK) Retail and Technology GmbH. The data is part of GfK's Retail Panel on major domestic appliances (MDA) and consists of quantities and scanner prices at a model level on a monthly basis from January 2004 until January 2017 for 23 EU countries.[9] For a model in a given country-date (country-month-year combination), the price is a unit sales-weighted average across retailers, inclusive of value-added taxes and any discounts, while the quantity is the sum of unit sales across retailers. Due to a unique identifier (id) over time and across countries, a model's unit sales and prices can be observed in several countries simultaneously.[10]

For the purposes of our analysis, a downside of the GfK's MDA panel for the EU is its limited coverage of products' attributes.[11] For this reason, we complement the EU data with a secondary data set: the GfK's MDA Retail Panel for Russia. A distinct property of the Russian panel is that it incorporates a comprehensive set of refrigerator characteristics, described in detail in Table A.1, including brand name and, importantly, a

[9]The EU Member States that are not in the panel are Bulgaria, Cyprus, Ireland, Luxembourg and Malta.

[10]On average, the raw data covers close to 23,000 refrigerator models per year with an annual sales volume of 13 million units and a value of 8.3 billion Euro. The primary data accounts for about 70% of annual aggregate expenditure on cold appliances in the covered countries and years.

[11]The data set contains three product characteristics, namely: type of installation (built-in or free-standing), a size variable, which combines information on the number of doors, height range and freezer position, and the presence of a no-frost system. These features are insufficient to carry out an in-depth analysis of vertical product differentiation.

manufacturer's model number.[12] Merging the two data sets by model id, thus populating the European data with all available characteristics in the Russian panel, results in an intersection of 3,446 refrigerators.

A crucial advantage of working with products sold both in Russia and the EU is that, unlike the EU, the Eurasian Economic Union (EEU) requires information on the exact location in which goods sold on its territory are manufactured.[13] Thus, the intersecting sample can be augmented with data on models' country of manufacture (origin).[14] We acquire this information in several ways by exploiting a number of specific reporting requirements in the EEU. In particular, to access the territory of the EEU, products need to have a TR CU (EAC) Certificate of Conformity, which proves their compliance with the conditions stipulated in the technical regulations of the customs union. The EAC Certificate reports the name and location of a good's manufacturer and the exact production branch (if any), while an annex lists the model numbers of the certified products. We match model numbers in the GfK data to either an EAC Certificate, or to an instruction manual for an appliance, which is also a necessary requirement for certification and typically lists a country of origin. In addition, we web scrape data from several major Russian online stores.[15] In this manner, we manage to identify the country of origin for 2,684 refrigerators, or 77% of the models at the intersection of the Russian and EU Retailer Panels, which is the final estimation sample. To this data, we also add bilateral exchange rates expressing a unit of country-of-destination currency in terms of its country-of-origin currency value, which we later use to instrument prices.

Table 1 shows descriptive statistics of the primary data in Panel A. In Panel B, the data is restricted to models sold in at least two countries, which is the relevant sample against which to assess the representativeness of the estimation sample, summarized in

[12]Similarly to the European data, the Russian data covers close to 70% of aggregate spending of Russian consumers on refrigerators. Even though the Russian data is fairly exhaustive with respect to product attributes, its shorter time span (2011-2016), and the 60% devaluation of the Russian ruble in 2014, render it unsuitable for the objectives of the present paper. The devaluation occurred as a result of several political developments, herein Russia's annexation of Crimea in 2014 and the subsequent sanctions imposed on it by the international community, combined with a sharp drop in the price of oil in early 2014. Consumers' rush to buy durable goods in anticipation of price hikes, and any composition effects due to shifts from imported to domestic goods could affect market shares and prices in ways that would compromise quality inference, as discussed below. Goetz and Rodnyansky (2021), who study the 2014 devaluation episode, demonstrate changes in quality composition for apparel.

[13]The EEU is a customs union (since 2010) and a common market (since 2012) between Armenia, Belarus, Kazakhstan, Kyrgyzstan, and Russia.

[14]Given that intermediate inputs can be produced in numerous locations, what we likely observe is a country of assembly/export.

[15]In the process of assignment of models' country of origin, we also make use of factory location by brand. Some brands have a single manufacturing location. A detailed explanation of the steps entailed in assembling the country of origin data is provided in the Online Appendix. See also Figure A.5 in the Online Appendix for an example of a Certificate of Conformity.

Table 1 – Descriptive Statistics

	Mean	Standard Deviation	Minimum	Maximum	N
	Panel A. Primary Data: Full Sample				
Unit sales	50.52	(158.06)	1	13,096	2,406,880
Price (Euro)	667.40	(478.87)	0.01	16,452	2,522,908
№ destination countries	5.28	(4.95)	1	23	4,813,735
	Panel B. Primary Data: Refrigerators sold in two or more countries				
Unit sales	44.65	(127.74)	1	7,276	1,728,751
Price (Euro)	691.56	(484.28)	0.36	13,284	1,806,850
№ destination countries	7.15	(4.86)	2	23	3,346,342
	Panel C. Estimation Sample				
Unit sales	43.75	(132.57)	1	7,089	364,713
Price (Euro)	759.20	(571.56)	1	10,888	364,713
№ destination countries	11.42	(5.32)	2	23	364,713
№ countries of origin	17.81	(2.18)	3	23	364,713
$\ln(ER)$	0.458	(2.48)	-5.76	9.65	289,583
$\ln(m)$	-8.14	(1.75)	-12.83	-2.04	364,713

Notes: The table provides summary statistics per product per country per month averaged over time, countries, and products. Panels A and B refer to the primary data with the following transformation applied in both panels: Refrigerators with one door and height of 90 cm or below are dropped. In Panel B the data is restricted to products traded in at least two countries. Panel C is composed of all models in the primary data, which are also present in the Russian Retail Panel. Panel C excludes all refrigerators without a freezer as well as refrigerators with a height less than 105 cm. In all three panels, negative or zero units and prices are replaced with missing observations. Units smaller than one are also replaced with missing values. For Estonia, Slovakia, and Slovenia, data is dropped for the years ≤ 2011, ≤ 2008, and ≤ 2006, respectively, to avoid any confounding effects of these countries' membership into the European Monetary Union. For the sake of comparability, all prices are reported in Euro, but in all subsequent estimations, prices are in the respective national currency. № destination countries are the average number of countries in which refrigerators are sold. The data consists of 23 destination countries, with the following composition in Panel C: Poland (11.35), Czech Republic (9.04), Germany (8.87), Hungary (6.00), Austria (5.49), Italy (5.37), Lithuania (5.08), Spain (5.00), France (4.85), the Netherlands (4.43), Belgium (4.41), Croatia (3.84), Slovenia (3.60), Slovakia (2.92), Latvia (2.57), Portugal (2.57), Denmark (2.55), Greece (2.50), Sweden (2.42), Finland (2.19), Romania (1.70), the United Kingdom (1.67), Estonia (1.58). The data consists of 28 countries of origin, with the following composition in Panel C: Germany (28.71), Italy (14.87), Bulgaria (10.46), Russia (8.90), Poland (7.07), Hungary (6.1), South Korea (4.15), China (3.17), Slovenia (2.64), Austria (2.31), Turkey (2.2), Serbia (1.96), Romania (1.52), Lithuania (1.27), Sweden (1.23), Belarus (0.90), Brazil, Spain, Czech Republic, Denmark, France, Greece, Mexico, Indonesia, Ukraine, Slovakia, Taiwan, combined (2.54). Numbers in parentheses after country names are the number of observations associated with the respective country of destination/origin as a percent of total observations in the estimation sample in Panel C. $\ln(ER)$ is the natural logarithm of the bilateral destination-origin exchange rate. $\ln(m)$ is a country-, model-, date-specific market share calculated from the raw data set replacing negative and unit values smaller than one with missing observations. Country time coverage in all panels is: Jan. 2004-Sept. 2013–Belgium Denmark, France, Finland, Italy, the Netherlands, Portugal, Spain, Sweden, the UK; Jan. 2004-Jan. 2017–Austria, Croatia, Czech Republic, Germany, Hungary, Poland; Jan. 2006-Sept.2013–Latvia, Lithuania; Jan. 2006-Dec. 2010–Estonia; Jan. 2007-Jan. 2017–Slovenia; Jan. 2009-Sept. 2013–Romania, Slovakia.

Panel C. Note that given the method of generation of the estimation sample, models sold in only one country drop out automatically. Even though, as shown in Figure A.1, single-country refrigerators account for more than 60% of all models on the European Common Market in a given year, their importance is diminishing over time, with sales of products traded in multiple countries reaching 70% of all units sold in 2012-2013.[16] Further, single-country products are more likely to be retailer-specific or local brands with limited vertical differentiation.[17] t-tests comparing means of unit sales and prices in the estimation sample to the remaining products in Panel B do point at statistically significant differences. In magnitude, these are modest for units, but prices, on average, tend to be about 10% higher in the estimation sample. Considering the larger number of destinations in which products in Panel C are present, the price differential might be explained if additional markets are consistently farther away from countries of origin and/or are higher-income destinations.[18] Assuming that prices are a good indicator of quality, Figure A.2 in the Appendix, which traces the evolution of market shares across a large number of price quantiles, shows that also in terms of quality composition the estimation sample is largely comparable to that of the sample summarized in Panel B.

Table 2 provides descriptive statistics of the physical attributes in the data. All in all, the sample exhibits substantial variability in attributes. Close to half of the refrigerators in the estimation sample have a no-frost system, while about 40% have a display and a metal(-like) front decoration. Fresh produce storage (zero-degree box) is present in 17% of the models. Less frequent are side-by-side design and the presence of ice/water dispensers (both in 6% of the sample). In terms of the energy rating distribution, the vast majority of the refrigerators are split between the energy labels A, A+ and A++, with smaller shares of appliances present in the most efficient category (A+++) and the least efficient one (B/C/D).

3 Demand Side Analysis

This section presents a demand-side framework with representative consumers from several destination countries displaying constant elasticity of substitution (CES) utility. We apply this framework to the refrigerators market to infer quality at the model level. The standard CES preference framework used in this section imposes homothetic demand schedules across all destination countries. In the next section, we relax this restriction and allow for the presence of nonhomotheticicities linked to the quality dimension.

[16]This trend is reinforced by an increasing number of countries in which products are marketed– 5 countries in 2012, on average, compared to 1.6 countries in 2004.

[17]For example, 17% of single-country products in the data are retailer brands, which are identified by a specific letter in their id number.

[18]This would be in line with the " shipping the good apples out" effect as discussed, e.g., in Hummels and Skiba (2004).

Table 2 – Descriptive Statistics: Physical Characteristics

	Mean	Standard Deviation	Minimum	Maximum	N
	Estimation Sample				
log Noise level (dB)	3.70	(0.06)	3.43	4.60	356,724
No-frost system	0.47	(0.50)	0	1	364,615
Freezer side	0.06	(0.25)	0	1	364,713
Water/ice-cube dispenser	0.06	(0.23)	0	1	364,713
Zero-degree box	0.17	(0.38)	0	1	363,182
Display	0.39	(0.49)	0	1	349,915
Annual energy use (kWh)	305.67	(78.46)	80	694	340,895
№ doors	2.00	(0.34)	1	4	364,713
Metal exterior	0.36	(0.48)	0	1	364,713
Energy label	0 B,C,D (1.5); 1 A (26.0); 2 A+(56.9); 3 A++ (14.0); 4 A+++ (1.7)				364,564
Width	0 <51cm (1.3); 1 51-56 (29.4); 2 57-62 (55.6); 3 63-72 (4.1); 4 >72 (9.6)				364,453
Liters	42-199 l (2.2); 200-299 (44.2); 300-399 (41.7); ≥400 (12.0)				364,708

Notes: Noise level is measured in decibel, and annual energy consumption in kilowatt-hour. No-frost, freezer side, zero-degree box, display, and metal exterior are binary variables equal to one if a refrigerator has a no-frost system, a freezer located on the side, a zero-degree compartment, a display, and metal/metal looking front decoration, respectively, and 0 otherwise. The categorical variables energy label, width and liters are summarized by describing their distributions. For these variables, numbers in parentheses are the percentage of each level from total observations. For a detailed description of all physical characteristics and their separation into vertical, horizontal and size-related features, refer to Table A.1 in the Appendix.

3.1 A Model of Homothetic Consumer Choice

We consider a demand-side setup with a set of destination countries indexed by $i \in \mathcal{I}$. Each destination country is populated by a continuum of households. There is a representative household for each country i. The supply side comprises a finite number of different goods (or sectors) indexed by $s \in \mathcal{S}$. Each good s is available in several varieties, indexed by $j_s \in \mathcal{J}_{s,t}$, where $\mathcal{J}_{s,t}$ denotes the set of varieties of good s available in period t.

We summarise the representative household's preferences by a two-tier consumption aggregator $Y_{i,t}$. The upper-tier bundles different goods according to a Cobb-Douglas function with sectoral shares $\alpha_s \in (0,1)$. The lower-tier aggregates *varieties* of each good s according to a CES function with elasticity of substitution across varieties $\sigma_s > 0$. Formally:

$$Y_{i,t} = \prod_{s \in \mathcal{S}} \left[\left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s}, \tag{1}$$

where $\lambda_{i,j_s,t}$ is a demand shifter specific to country i, variety j_s and period t, and $q_{i,j_s,t}$ denotes the quantity consumed of variety j_s in country i in period t.

Henceforth, we assume that $\lambda_{i,j_s,t}$ comprises three separate components, namely

$$\lambda_{i,j_s,t} = \exp\left(\theta_{j_s} + \varsigma_{i,j_s} + \upsilon_{i,j_s,t}\right). \tag{2}$$

Each component in (2) aims at capturing different sources of taste shocks. The term $\upsilon_{i,j_s,t}$ is an i.i.d. zero-mean taste shock specific to country i, variety j_s and period t. The term ς_{i,j_s} is a time-invariant taste shifter specific to country i and variety j_s, which averages out to zero across the set of countries. These assumptions imply that one can interpret θ_{j_s} as capturing the *intrinsic* quality of variety j_s – that is, the quality of variety j_s after removing country-specific and country-period-specific shocks.

From the first-order conditions of the representative household's problem based on (1), and bearing in mind (2), the quantitative market share of variety j_s in country i in period t can be derived as:

$$m_{i,j_s,t} \equiv \frac{q_{i,j_s,t}}{Q_{i,s,t}} = p_{i,j_s,t}^{-\sigma_s} \Omega_{i,s,t} e^{\theta_{j_s} + \varsigma_{i,j_s} + \upsilon_{i,j_s,t}}, \tag{3}$$

where $\Omega_{i,s,t} \equiv \left(\sum_{j_s \in \mathcal{J}_{s,t}} p_{i,j_s,t}^{-\sigma_s} \lambda_{i,j_s,t} \right)^{-1}$, and $Q_{i,s,t} \equiv \sum_{j_s \in \mathcal{J}_{s,t}} q_{i,j_s,t}$. (See Appendix A.1.1.1 for a complete derivation of (3).) Taking logarithms of (3), we obtain the following linear equation:

$$\ln m_{i,j_s,t} = -\sigma_s \ln p_{i,j_s,t} + \mu_{i,t} + \theta_{j_s} + \varsigma_{i,j_s} + \upsilon_{i,j_s,t}, \tag{4}$$

where $\mu_{i,t} \equiv \ln \Omega_{i,t}$. Equation (4) constitutes the starting point of our empirical analysis. Given that we will henceforth focus on the refrigerators market, to ease notation, we drop the sectoral subscript s. In addition, we will from now on refer to $j \in \mathcal{J}_t$ as a specific refrigerator *model*.

3.2 Empirical Framework: Inferring Quality

Since the country-model dummies nest θ_j, equation (4) can be re-written as:

$$\ln m_{i,j,t} = -\sigma \ln p_{i,j,t} + \mu_{i,t} + \phi_{i,j} + \upsilon_{i,j,t}, \tag{5}$$

where $\phi_{i,j} \equiv \theta_j + \varsigma_{i,j}$. $\phi_{i,j}$ control for any time-invariant model-specific unobservables across countries, and likewise, for time-invariant shocks across models in each destination. These fixed effects, therefore, will absorb the impact of attributes such as brand, energy efficiency, country of origin and others, generally viewed by consumers as signals of product quality and performance. They will also control for any time-invariant country-specific taste for certain specific attributes or brands. The country(destination)-date fixed effects $\mu_{i,t}$ account for time-varying country-specific shocks that are common across models, and also accommodate the possibility of a differential impact of shocks across countries within a month-year. Thus, they capture destination-specific seasonality and any macroeconomic developments that can affect sales, namely changes in unemployment rates, value-added taxes, and income per capita, amongst others. The dependent variable, $\ln m_{i,j,t}$ is the natural logarithm of the market share of model j in destination i at date t, where the denominator of m, the total number of units sold in date t in country i, is calculated based on the full data set summarized in Panel A of Table 1. Given the fixed effects used in 5, the price elasticity of demand σ is identified from time variation in relative prices within a model within a country.

Equation (5) constitutes the standard demand-side approach to inferring quality formulated by Khandelwal (2010). The intuition behind this method is that conditional on price, higher quality products command larger market shares. Quality measures can thus be obtained by averaging residual demands for each model in each market across countries and time, after netting out the impact of prices and that of country-period fixed effects. Formally:

$$\widehat{\theta}_j = \frac{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \ln m_{i,j,t} - (-\widehat{\sigma} \ln p_{i,j,t} + \widehat{\mu}_{i,t})}{N \times T}, \tag{6}$$

where N denotes the number of countries and T the number of periods in the sample.

Although the specification in (5) explicitly accounts for the confounding effect of product features through the incorporation of $\phi_{i,j}$, any time-varying model-specific demand shifters such as shocks to reputation, environmental image, and others remain in the error term. This would likely induce a positive correlation between $\upsilon_{i,j,t}$ and price, and would therefore lead to a biased and inconsistent OLS estimate of σ.[19] In turn, since higher quality models are presumably more costly to produce and command higher mark-ups, prices would also tend to be positively correlated with $\phi_{i,j}$ resulting in a biased quality estimate of $\widehat{\theta}_j$ as well.

To deal with price endogeneity, we exploit the fact that we are able to trace the country where the plant producing model j is located (country of origin k of model j). Provided that changes in bilateral exchange rates over time, $ER_{k,i,t}$, are at least partly passed through into consumer prices, they can serve as a source of exogenous variation in retail prices in their destination markets.[20] Note that in the current framework, ideally, an instrumental strategy would rely on model-specific cost shifters to identify model-specific price variation. Within destination i, bilateral exchange rate volatility generates cost fluctuations only at the level of a group of products characterized by the same country of origin. Table 1 shows that, on average, models in a given destination country originate from 18 different locations within a year. Nevertheless, some models are manufactured domestically, i.e. $k = i$, while others are imported from countries with the same currency (given the use of the Euro as the common currency of the Eurozone). In these cases, our instrumental variable will not exhibit any variation across time.

Formally, in a two-stage least-square estimation, in which model j's price is instrumented with the amount of k's currency that one unit of i's currency can purchase at date t, the first stage equation is:

$$\ln p_{i,j,t} = \beta \ln ER_{k,i,t} + \delta_{i,j} + \tau_{i,t} + \varepsilon_{i,j,t}, \tag{7}$$

[19] For example, the sudden spread of bad news related to a given manufacturer could translate into a negative preference shock for models produced by that manufacturer, while sellers could respond to the shock by (temporarily) cutting prices of the affected products. Similarly, model-specific variation in marketing aggressiveness across manufacturers over time, or specific policies (like targeted subsidies, minimum performance standards as stipulated in the European Ecodesign Directive, etc.), could all simultaneously impact prices and market shares. Finally, time trends in preferences for certain attributes of a model could lead to fluctuations in its price until the manufacturer has had enough time to respond to those trends by adjusting their production line accordingly.

[20] Similarly, Piveteau and Smagghue (2019) make use of the different sets of countries a firm sources its inputs to instrument for firm-variety-specific export prices and infer quality at the firm level. In a structural model of the coffee industry, Nakamura and Zerom (2010) instrument retail coffee prices with bilateral exchange rates.

If model j's production cost is to some extent determined by factor prices in its country of origin k, then an increase in $ER_{k,i,t}$, indicating depreciation of k's currency would make k's goods sold in i cheaper. We expect, therefore, that $\beta < 0$. In terms of the exclusion restriction, it is hard to think of a compelling mechanism through which the exchange rate could impact market shares other than indirectly via its ensuing effect on prices in the destination market. Additionally, the possibility of reverse causality from $m_{i,j,t}$ on $ER_{k,i,t}$ is remote. Such a threat to the exogeneity of the instrument would require demand in country i for refrigerators produced in country k to be large enough relative to the sizes of those two economies that shocks affecting $m_{i,j,t}$ would also have an impact on the bilateral exchange rate.

3.3 Estimation Results and Residual Decomposition

Table 3 reports the results from the estimation of eq. (5), where the price is instrumented with the bilateral nominal exchange rate between a model's sale destination and its country of origin. The specification is augmented with brand-year indicators in an attempt to capture time-varying demand shocks at the brand level that could affect prices and market shares simultaneously.

Given the likely positive correlation between prices and the error term, the price elasticity estimated via OLS would be biased towards zero. This is confirmed in Column (1), which yields a demand curve with an elasticity of 0.59. Column (2) instruments the log of price with the current and three lags of the logarithm of the exchange rate allowing for the possibility of a non-instantaneous adjustment of retail prices to exchange rate fluctuations. Our choice of the number of lags is guided by previous findings in the literature on the speed of the exchange rate pass-through, which indicate that prices respond within a quarter (e.g., Campa and Goldberg, 2005) or even faster (e.g., Bonadio, Fischer, and Sauré, 2020). Since we allow for intra-cluster dependence at various levels, and as homoskedastic errors are unlikely, we employ the effective F-statistic of Montiel Olea and Pflueger (2013) to judge the strength of the IV. For a threshold $\tau = 10\%$, the F-statistic 15.29 exceeds the TSLS critical value of 11.64, so that the null of weak instruments is rejected. Nevertheless, given that the first-stage results in Column (2) show that neither the contemporaneous, nor the first two lags of ER are statistically significant, we choose a more parsimonious specification using only the third lag as an excluded instrument.[21]

[21] The lack of significance of the coefficients associated with the contemporaneous, first and second lag of the monthly exchange rate in column (2) are due to the high degree of serial correlation between those variables. The estimation results in Table 2 remain robust to changing the number of lags of the exchange rate in column (2), or to using the first or second lag of the exchange rate in columns (3)–(6).

Table 3 – Inferring Quality

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			2SLS		
				ER $\neq$1		ER $\neq$1
		A. Second Stage				
ln(Price)	-0.059	-3.851	-4.753	-6.090	-4.753	-6.090
	(0.025)**	(1.308)***	(1.420)**	(1.851)***	(2.193)**	(2.510)**
Anderson-Rubin 95% CI		[-5.72,-2.79]	[-7.99,-2.28]	[-10.60,-3.02]	[-12.13,-1.02]	[-13.53,-1.03]
		B. First Stage				
ln(ER)		-0.020				
		(0.015)				
L^{-1} ln(ER)		0.005				
		(0.024)				
L^{-2} ln(ER)		0.015				
		(0.024)				
L^{-3} ln(ER)		-0.050	-0.045	-0.039	-0.045	-0.039
		(0.016)***	(0.007)***	(0.007)***	(0.014)***	(0.012)***
Olea Pflueger Eff. F-stat.		15.29	46.28	31.98	11.22	9.77
Products	2,908	2,217	2,217	1,986	2,217	1,986
Clusters	2,682	2,605	2,605	2,604	23	23
N	364,697	284,025	284,025	185,126	284,025	185,126

Notes: The table shows results from a 2SLS estimation in which ln(Price) is instrumented with the contemporaneous and three lags (column(2)) or only the third lag of the logarithm of the exchange rate between the country where a model is sold (destination) and the country where it is manufactured (origin). All specifications include country of destination-date, product-country of destination, and brand-year fixed effects. Column (1) is an OLS regression. The dependent variables are log(Price) in the first stage, and the logarithm of the market share in the second stage. The market shares are based on the full sample described in Panel A of Table 1. Columns (4) and (6) exclude all products whose destination/destination currency is the same as their origin/country-of-origin currency. Standard errors in parentheses are robust in all specifications and clustered by country of destination-date in Columns (1)-(4) and by country in Columns (5)-(6). All 2SLS specifications additionally report 95% weak-IV-robust Anderson-Rubin confidence intervals implemented with `rivtest` and `itercenter` by Rios-Avila (2015) . * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In this just-identified case, the effective F-statistic coincides with the robust Kleibergen-Paap Wald F statistic, and, following Andrews, Stock and Sun (2018), we evaluate the IV's performance on the basis of Stock-Yogo critical values. Note that importantly all specifications additionally report weak-identification-robust, and in the just-identified case, also efficient Anderson-Rubin confidence intervals (Finlay and Magnusson, 2009). Since these intervals are based on test inversion and not point estimates and standard errors, they are valid even in the presence of weak instruments (Andrews, Stock and Sun, 2018). Column (3) reports a larger estimate of the price elasticity of 4.75 when the endogenous regressor is exactly identified.[22] Limiting the sample to sales whose destination-origin country pair is such that the instrument varies over time in Column (4) leads to a higher estimate of 6.1.

The estimated exchange rate pass-through into retail prices reported in Panel B ranges between 4% and 5%, and is comparable to other sector-specific findings in the literature. Antoniades and Zaniboni (2016) estimate a pass-through between 4% and 6% within a four-month period using microdata on fast-moving consumer non-durables. For beer, Goldberg and Hellerstein (2013) find a pass-through of 7%, showing that rigidity in wholesale prices predominantly driven by local non-traded goods and adjustment costs explain the very limited pass-through by retailers. At the second stage, the price elasticity in Column (3) is within the estimated range of structural demand-side models based on product-level data on market shares and prices. This literature generally obtains elasticities well above 2 (e.g., Piveteau and Smagghue, 2019; Goldberg and Hellerstein, 2013; Nakamura and Zerom, 2010; Broda and Weinstein, 2006). Our point estimate of 4.75 is identical to Broda and Weinstein (2006)'s elasticity of substitution for differentiated goods, and slightly higher than their average estimate for the 6-digit HS product category 'combined refrigerator-freezers, fitted with separate external doors' (HS-6 841810).

Since the instrument varies by destination-origin-date, Columns (2)-(4) cluster standard errors at the intersection of destination-date (country $\cap$ date), thus treating observations in the same country but in different dates as independent. In spite of the extensive set of fixed effects incorporated in the estimation, it is likely that this restriction leaves unaccounted for intra-cluster correlation. This is confirmed in the next two columns, which

[22]It is possible that variation in the bilateral exchange rate leads to heterogeneous price responses across models with different levels of quality. For the wine sector, Chen and Juvenal (2016) find that the exchange rate pass-through into prices decreases with product quality, while Chatterjee et al. (2013) demonstrate that price adjustments can be heterogeneous even within multi-product firms depending on a product's proximity to the core competency of a firm. To test for differential pass-through, we interact the instrumental variable with two proxies for quality. In the first specification, we separate products based on their country of origin, assuming that models manufactured in Western Europe or South Korea are of higher quality than those produced in developing economies. The second specification generates a dummy variable equal to one for high energy efficiency models (labels A++and A+++). Neither of the interaction terms proves statistically significant, as shown in Table A.2 in the Appendix.

Table 4 – Placebo Test: Random Assignment of Country of Origin

	Sign		p-value$\leq$0.05	
	Positive	Negative	Positive	Negative
	First Stage Coefficient L^{-3} ln(ER)			
Specification (3)	50.9	49.1	2.6	1.4
Specification (4)	51.0	49.0	3.2	1.7
	Second Stage Coefficient ln(Price)			
Specification (3)	49.9	50.1	0.1	0.0
Specification (4)	50.1	49.9	0.1	0.0

Notes: Specifications (3)-(4) from Table 3 are replicated 1000 times each, both for the first and second stage of the 2SLS estimation. In each replication, L^{-3} ln(ER) are randomly shuffled relative to the remaining variables in the data, which is equivalent to a random assignment of a country of origin to each model. The table reports the number of replications (in percentage) yielding a positive or a negative sign of the coefficients on L^{-3} ln(ER) and ln(Price) in the first and second stages of the estimation, respectively, and the percentage of positive and negative outcomes that are statistically significant at 5% or more.

allow for arbitrary patterns of serial correlation in the residuals by clustering at the coarser level of country: Compared to earlier specifications, standard errors increase by about 40-50% in the second stage, and almost double in the first stage. The corresponding effective F-statistics are lower and approach the benchmark of 10. The Anderson-Rubin confidence interval for our preferred specification in Column (5) excludes elasticities smaller than one and is 29% wider than the non-robust Wald CI. We reject values of σ below one and over 12 at the 5% level.

The identification strategy rests crucially on whether exogenous volatility in bilateral exchange rates between the plant where a given model is manufactured and the destination markets where it is sold is reflected in consumer prices. The first-stage results reported in Table 3 confirm a partial pass-through. As a robustness check, Table 4 performs a falsification exercise by randomly reshuffling the bilateral exchange rate relative to the remaining variables in the data set, thus equivalently randomly assigning a country of origin to a model-date cell. This placebo test is performed 1000 times for specifications (3)-(4) in Table 3, with the table showing the percent of replications yielding positive or negative coefficients in the first and second stage of the 2SLS, and the share of these with statistical significance at 5% or higher. Since all standard errors are clustered at the intersection of country-date, given the results and discussion in Table 3, t-tests of the null hypothesis that prices have no effect on unit sales would tend to over-reject, thus working against the placebo. Nevertheless, Table 4 clearly demonstrates that the demand elasticity is identified solely from responses in relative market shares to changes in relative prices stemming from bilateral exchange rate fluctuations.

In another robustness check, we explore the sensitivity of the price-elasticity estimates to changes over the life-cycle. Figure A.3 in the Appendix demonstrates that unit sales of cohorts of products introduced in a given year follow approximately bell-shaped curves over their life-cycle, while average prices generally decline with product-age. The precise position of products along their life-cycle can be a confounding factor if, for example, a high-quality group of models nearing the end of their life-cycle and thus commanding small market shares and possibly lower prices is estimated to be of lesser quality as a result. To address this issue, we can augment eq. (5) with $mage_{y,i}$, where y are relative-distance-in-years-from-first-year fixed effects measured as the number of years a model is on the market in a given country since its entry, which we interact with country-specific indicators. Table A.4 in the Appendix reestimates the last two specifications of Table 3 taking into account the age variable. The resulting elasticity parameter estimates are slightly lower, although the confidence intervals overlap with our baseline estimates.

3.3.1 Residual Decomposition Analysis: Unpacking Quality

We next conduct a decomposition analysis of quality measures obtained as residuals from the 2SLS estimation in Section 3.3 on a large set of model attributes. The main objective is to assess whether attributes with a clear vertical dimension explain a significant amount of variation in quality. In other words, we check whether consumers perceive such characteristics as determinants of quality, keeping all else equal.

To explore the relationship between estimated quality and product features, we standardize the quality measures obtained from (6) and use them as a dependent variable in the specification:[23]

$$\widehat{\theta}_j = b_j + \sum_{c=1}^{n} \alpha_c x_{c,j} + \epsilon_j, \tag{8}$$

where b_j is a brand fixed effect. α_c captures the effect of the c-th attribute $x_{c,j}$ on the quality index relative to a model without the attribute, or for a unit change in the attribute, holding all else constant. Specifically, we assess the following characteristics, which contribute to vertical appliance differentiation: the availability of a no-frost system, a display, a freezer on the side, a water/ice dispenser, a metal exterior and a zero-degree box, as well as the level of energy efficiency and noise. The data additionally contains a variety of size measures summarized in Table A.1. Given the naturally high level of collinearity between the size characteristics, we focus on the number of doors as a single size indicator. With the exception of noise, we expect a positive correlation

[23]For the 2,069 products that enter the estimation in Table 5 the index is close to normally distributed, as shown in Figure A.4

Table 5 – Determinants of Inferred Quality

	Inferred Quality					log(Price)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Energy label	0.135			0.217	0.222		
	(0.026)***			(0.030)***	(0.030)***		
A+++		0.599				0.145	0.243
		(0.137)***				(0.063)**	(0.071)***
A++		0.313				0.017	0.160
		(0.114)***				(0.066)	(0.072)**
A+		0.153				-0.045	0.020
		(0.099)				(0.046)	(0.047)
A		0.067				-0.048	-0.044
		(0.087)				(0.040)	(0.042)
ln(kWh)			-0.047				
			(0.100)				
Zero-degree box	0.345	0.342	0.379	0.323	0.322	0.214	0.207
	(0.145)**	(0.144)**	(0.165)**	(0.096)***	(0.098)***	(0.094)**	(0.056)***
Freezer side	0.811	0.814	0.864	0.845	0.847	0.549	0.529
	(0.058)***	(0.061)***	(0.068)***	(0.065)***	(0.060)***	(0.052)***	(0.035)***
Dispenser	0.242	0.245	0.189	0.287	0.269	0.120	0.157
	(0.077)***	(0.077)***	(0.097)*	(0.060)***	(0.058)***	(0.063)*	(0.037)***
No-frost system	0.282	0.276	0.364	0.275	0.275	0.224	0.213
	(0.102)***	(0.098)***	(0.103)***	(0.076)***	(0.079)***	(0.049)***	(0.036)***
ln(Noise Level)	-1.474	-1.433	-2.594	-1.572	-1.538	-0.454	-0.827
	(0.623)**	(0.616)**	(0.711)***	(0.566)**	(0.573)**	(0.338)	(0.305)**
Display	0.223	0.222	0.233	0.197	0.195	0.202	0.173
	(0.026)***	(0.026)***	(0.030)***	(0.034)***	(0.034)***	(0.026)***	(0.028)***
Metal exterior	0.099	0.101	0.105	0.134	0.133	0.054	0.105
	(0.038)**	(0.038)**	(0.038)**	(0.045)***	(0.045)***	(0.015)***	(0.024)***
№ doors	0.391	0.395	0.338	0.360	0.368	0.198	0.159
	(0.048)***	(0.048)***	(0.046)***	(0.050)***	(0.050)***	(0.041)***	(0.032)***
Destination-date	No	No	No	Yes	Yes	No	Yes
Origin-date	No	No	No	Yes	Yes	No	Yes
Brand	Yes	Yes	Yes	Yes	No	Yes	No
Brand-Year	No	No	No	No	Yes	No	Yes
N	2,069	2,069	1,636	272,528	272,527	2,069	272,527
R^2	0.661	0.662	0.677	0.558	0.565	0.774	0.835

Notes: The dependent variable is inferred quality, $\widehat{\theta}_j = (\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \ln m_{i,j,t} + \widehat{\sigma} \ln p_{i,j,t} - \widehat{\mu}_{i,t})/(NT)$, in columns (1)-(3), and $\widehat{\theta}_{ijt} = \ln m_{i,j,t} + \widehat{\sigma}_{2SLS} \ln p_{i,j,t} - \widehat{\mu}_{i,t}$ in columns (4)-(5), as estimated in Table 3, and log(Price) in Euro in Columns (6)-(7). In columns (1)-(3) and (6), the data is collapsed at product level. Physical characteristics are explained in Table A.1, while Table 2 provides descriptive statistics. All standard errors are robust and clustered by brand in columns (1)-(3) and (6), and two-way clustered by brand and country in columns (4)-(5) and (7). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

between a feature availability and $\widehat{\theta}_j$ such that $\alpha_c > 0$. As quieter compressors, evaporator and condenser fans are technologically superior (e.g., single-speed vs. digital inverter compressors), noisier refrigerators would generally imply lower product quality.

The results of this exercise are reported in Table 5. The first three columns use as dependent variable the quality measures at product-level according to (6), and show OLS estimates with brand fixed effects. Columns (4) to (5) use instead $\widehat{\theta}_{ijt} = \ln m_{i,j,t} + \widehat{\sigma} \ln p_{i,j,t} - \widehat{\mu}_{i,t}$ as a dependent variable. In these two cases, we incorporate destination-date and origin-date fixed effects. The key performance attributes determining quality as discussed above enter as explanatory variables, where zero-degree box, freezer side, dispenser, no-frost system, display, and metal exterior are binary indicators, kWh and noise are continuous variables, and energy label is coded as an ordinal variable with higher values assigned to more efficient labels. The table shows that features consumers would perceive to enhance (reduce) quality are found to be positively (negatively) correlated with the dependent variable. For instance, adding one more door to a refrigerator increases the quality measure by 0.4, while a 10% rise in the noise level leads to a 0.2 reduction.

Column (2) allows for a non-linear effect of the energy label by introducing a dummy variable for each label, with B, C or below efficiency grades serving as a reference category. The effect on quality is strongest for the highest efficiency labels A++, and especially A+++. As briefly explained in Table A.1, the European cooling appliances label is attributes-based, which means that the effect of size, and the presence of specific features are accounted for when the efficiency level is assigned. Thus, even though a high-quality refrigerator is likely to consume more energy by virtue of its attributes, the label still likely rates it as highly energy efficient. In this regard, to confirm that it is indeed the energy efficiency rating that consumers focus on (rather than the crude measure of energy consumption), in Column (3), we enter a single determinant of energy consumption unadjusted for characteristics –a model's annual kWh consumption. While having the expected sign, the coefficient of this attribute is not statistically different from zero.

Models of differentiated product markets consider prices to be a function of product characteristics. Results from hedonic regressions are reported in Columns (6) at the product-level, and Column (7) for the panel. While preserving the correct signs, the estimated implicit prices now yield marginal valuations of the constituent attributes in terms of their contribution to price, and are interpreted as semi-elasticities or elasticities for the variables in log. If prices are used as a proxy for quality, comparing the parameter estimates of Columns (2) and (6) reveals some qualitative and quantitative differences. High energy efficiency, for example, exerts a significant and economically meaningful effect on the quality measure, which is less pronounced in the aggregated hedonic specification.

Likewise, the coefficient on the noise level turns statistically insignificant. Column (7) demonstrates that the estimated relationships in a hedonic setting are more sensitive to the level of aggregation than the inferred quality measures. These results highlight some of the pitfalls of using prices as an indicator of quality in a setting that aims to determine attributes' individual impact on quality.

Given the wide applicability of the methodology that infers quality from consumer choices to various sectors and settings, the results in Table 5 also convey two important and related messages regarding this methodology's performance. First, they show that the set of main vertical attributes, including the brand name, explain close to 70% of the variation in inferred quality. Second, the fact that each of the main attributes affects the quality measure significantly serves as an external validation of the methodology by demonstrating that residual demands do reflect the impact of underlying objective attributes with a clear vertical order.

4 Income and Choice of Quality

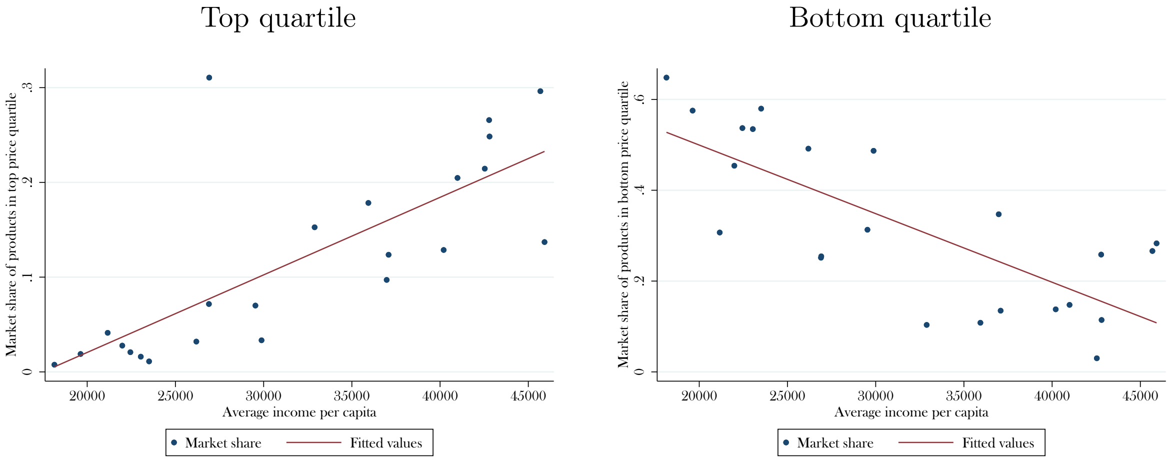
The previous analysis was conducted within a homothetic demand-side framework. As a result, it did not allow for income to (heterogeneously) affect consumers' willingness to pay for varieties differing in their intrinsic quality. This section investigates the accuracy of the homotheticity assumption. Our regression analysis infers quality from consumers' purchase decisions across destination markets with wide income disparities. Allowing for nonhomotheticities along the quality dimension is thus critical. We next demonstrate that our data clearly show patterns consistent with this hypothesis and then proceed with the regression analysis.[24]

Patterns in the raw data clearly show evidence consistent with nonhomothetic preferences. Categorizing prices into four quantiles, Figure 1 plots market shares against average income per capita in the destination countries of products in the lowest and the highest quartiles. Assuming that prices are a good proxy for quality, the figure points to a systematic variation in the quality of products demanded at different levels of income. Specifically, consistent with nonhomotheticity, market shares of high (low) quality goods are larger (smaller) in high income countries.

We now proceed to formally introduce and test for the presence of nonhomothetic preferences along the quality dimension. To that end, we expand the approach applied in

[24]Evidence consistent with nonhomotheticities along the quality dimension has been recurrently presented by studies relaying on unit values. In addition, income-dependent willingness to pay for quality is a feature that has been incorporated into several international trade models that sought to account for such type of income-effects in trade – see, e.g., Verhoogen (2008), Hallak (2010), Fajgelbaum, Grossman and Helpman (2011, 2015), Jaimovich and Merella (2012, 2015).

Figure 1 – Market Shares in Top and Bottom Price Quartiles vis-a-vis Income



Notes: The figure plots country-specific market shares of models in the highest (left) and the lowest (right) price quartiles in the estimation sample relative to income per capita as well as the predicted values of the market share by average per-capita income. Prices in the sample are measured in Euros. The average price in the bottom quartile is 156 (s.e. 132), and that in the top quartile is 1,426 (s.e. 679).

Section 3 with the nonhomothetic CES preference structure from Matsuyama (2019), and adapt it to a framework with vertically differentiated varieties.[25] Formally, let the consumption aggregator $Y_{i,t}$ be implicitly defined through the following expression:

$$\prod_{s \in \mathcal{S}} \left[\left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s} = 1. \tag{9}$$

The distinctive feature of (9) relative to (1) is the presence of the variety-specific parameters ε_{j_s}, which govern the income elasticity of variety j_s.[26] Note that one way to interpret $\lambda_{i,j_s,t}$ is as an income-independent demand shifter for variety j_s in country i at time t. The term $Y_{i,t}^{(\varepsilon_{j_s} - \sigma_s)/\sigma_s}$ will instead govern a demand shifter for variety j_s that is income-dependent.[27] Matsuyama (2019) shows that the term $Y_{i,t}^{(\varepsilon_{j_s} - \sigma_s)/\sigma_s}$ in (9) yields

[25] Matsuyama (2019) exploits the isoelastically nonhomothetic CES preferences to accommodate heterogeneous income elasticities across sectors. The utility function in (9) disregards such type of nonhomotheticity (by imposing a Cobb-Douglas structure across sectors), and focuses instead on allowing income elasticities to differ *across* varieties of goods *within* a given sector.

[26] Note that (1) is a special case of (9), which obtains from setting $\varepsilon_{j_s} = 1$ for all j_s.

[27] By defining $\widetilde{\lambda}_{i,j_s,t} \equiv \lambda_{i,j_s,t} Y_{i,t}^{\varepsilon_{j_s} - 1}$, where $\widetilde{\lambda}_{i,j_s,t}$ is a demand shifter that comprises an income-independent component ($\lambda_{i,j_s,t}$) and income-dependent component ($Y_{i,t}^{\varepsilon_{j_s} - 1}$), we could write (9) as

$$Y_{i,t} = \prod_{s \in \mathcal{S}} \left[\left(\sum_{j_s \in \mathcal{J}_{s,t}} \widetilde{\lambda}_{i,j_s,t}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s},$$

well-defined income effects on demand. Specifically, this term tends to place relatively more weight on consumption of varieties with larger values of ε_{j_s} as $Y_{i,t}$ grows.[28]

For notational clarity, we will henceforth let $\tilde{\varepsilon}_{j_s} \equiv \varepsilon_{j_s} - 1$. Moreover, given that the empirical analysis focuses solely on the refrigerators industry, once again, we drop the s subscript to ease notation. When preferences are given by (9), the optimization problem of country i's representative agent in t yields the following quantitative market shares:

$$m_{i,j,t} \equiv \frac{q_{i,j,t}}{Q_{i,t}} = p_{i,j,t}^{-\sigma} \, e^{\lambda_{i,j,t}} \, Y_{i,t}^{\widetilde{\varepsilon}_j} \, \widetilde{\Omega}_{i,t}, \tag{10}$$

where $\widetilde{\Omega}_{i,t} \equiv \left(\sum_{j \in \mathcal{J}_t} p_{i,j,t}^{-\sigma} \, Y_{i,t}^{\widetilde{\varepsilon}_j} \, \lambda_{i,j,t} \right)^{-1}$ and $Q_{i,t} \equiv \sum_{j \in \mathcal{J}_t} q_{i,j,t}$. Applying logs to (10), yields

$$\ln m_{i,j,t} = -\sigma \, \ln p_{i,j,t} + \widetilde{\varepsilon}_j \, \ln Y_{i,t} + \widetilde{\mu}_{i,t} + \lambda_{i,j,t}, \tag{11}$$

where $\widetilde{\mu}_{i,t} \equiv \ln \widetilde{\Omega}_{i,t}$.

The main difference between (11) and (4) lies in the fact that the former includes one additional term, $\widetilde{\varepsilon}_j \ln(Y_{i,t})$, which captures the impact of variety j's income elasticity (ε_j) on its (log) market share. Notice from (11) that, when $\varepsilon_j > 1$ $(\varepsilon_j < 1)$, the term $\widetilde{\varepsilon}_j \, \ln Y_{i,t}$ implies that model j's market share will increase (decrease) with real income. In addition, observe that when $\varepsilon_j = 1$ for all $j \in \mathcal{J}_t$, the expression in (11) boils down to (4). Thus, the demand structure stemming from the homothetic CES utility represents a *special* case of (9), when income elasticities are equal to one for all j.

The main goal of this section is to investigate whether such income effects can be linked to nonhomothetic preferences along the quality dimension. To this end, we tie the variety-specific parameters $\tilde{\varepsilon}_j$ to the intrinsic quality term associated with j. In particular, let

$$\tilde{\varepsilon}_j = \kappa\left(\theta_j\right), \tag{12}$$

where $\kappa(\cdot)$ is assumed to be a monotonic function with respect to θ_j. The presence of nonhomotheticicities would thus materialize as $\kappa'(\cdot) > 0$.

where this last expression can be seen to exhibit an analogous structure as (1), except that its demand shifter $(\widetilde{\lambda}_{i,j_s,t})$ includes an income-dependent component as well. Our log market shares regressions in this section will aim at identifying the demand shifter $(\widetilde{\lambda}_{i,j_s,t})$, after cleaning the impact of temporary country-time specific demand shocks.

[28]This feature of (9) resembles qualitatively the nonhomothetic specification used in Handbury (2021) within the context of a log-logit discrete choice model for grocery consumption.

4.1 Testing for the Presence of Nonhomotheticities

Combining (11) and (12), we could now test whether the demand schedules for refrigerators exhibit a nonhomothetic behavior along the quality dimension. To approach this question empirically, we further simplify (12) by assuming a linear relationship between $\widetilde{\varepsilon}_j$ and θ_j; namely, $\widetilde{\varepsilon}_j = \kappa \cdot \theta_j$.[29] Replacing this expression into (11), we can write:[30]

$$\ln m_{i,j,t} = -\sigma \, \ln p_{i,j,t} + \kappa \, (\theta_j \times \ln Y_{i,t}) + \widetilde{\mu}_{i,t} + \widetilde{\phi}_{i,j} + \widetilde{\upsilon}_{i,j,t}. \tag{13}$$

Note that if consumers' preferences were homothetic, then income elasticities should be *identical* across all fridge models *regardless* of their intrinsic quality θ_j. This would, in turn, be reflected by an estimate of the parameter κ in (13) that is not statistically different from zero.[31]

Column (1) of Table 6 displays the estimation results of (13) interacting $\ln Y_{i,t}$ –measured by country i's log-income per capita (in PPP)– with θ_j given by its estimate $\widehat{\theta}_j$ from (6) in Section 3. Column (1) reports two sets of standard errors: i) robust standard errors clustered at the country level in parentheses; ii) bootstrapped standard errors clustered at the country level in brackets. Clearly, since $\widehat{\theta}_j$ is a generated regressor resulting from the estimation of eq. (6), the first set of standard errors does not take into account the sampling variance of $\widehat{\theta}_j$, and is thus biased towards zero. Standard errors resulting from a non-parametric bootstrap estimation of both stages of the 2SLS based on 500 replications confirm that this is indeed the case. Given bootstrapped standard errors, the estimate of $\widehat{\kappa}$ is positive and highly significant, which implies that higher-quality fridge models tend to command relatively greater market shares in richer destination countries. Concerning the estimated price elasticity ($\widehat{\sigma}$), it remains negative and significant (albeit with a p-value slightly above 5%), while its point estimate is similar to that in Table 3.

The positive and highly significant κ in Column (1) clashes with the notion of demand homotheticity, suggesting the presence of nonhomothetic preferences along the quality dimension instead. In fact, Column (1) can be interpreted as a test of whether or not homothetic preferences are indeed an accurate representation of consumer behavior. The estimate of κ challenges the accuracy of the homothetic preference specification assumed

[29]As a robustness check, we also used a fourth-order polynomial expression for $\tilde{\varepsilon}_j = \kappa\,(\theta_j)$ interacted with log-income. The results yield a positive and significant estimate only for the linear term, whose point estimate is similar to the one displayed in Column (1) of Table 6.

[30]Note that the term $\widetilde{\phi}_{i,j}$ in (13) is formally different from $\phi_{i,j}$ in (5), since $\phi_{i,j}$ will implicitly absorb the impact of the average log-income on demand residuals for model j while $\widetilde{\phi}_{i,j}$ will not, given the explicit inclusion of the nonhomothetic term into (13).

[31]More precisely, under the null hypothesis that preferences are represented by (1), the regression equation (13) should yield an estimate of κ that is not significantly different from zero when using the 2SLS estimates $\widehat{\theta}_j$ obtained in Section 3 to measure model j's quality as done in column (1) later on.

Table 6 – Testing for Non-homothetic Preferences

Quality measure:	Homothetic	Non-homothetic	
	(1)	(2)	(3)
		1st Step	2nd Step
log(Price)	-5.273	-5.533	-3.462
	(2.305)**	(2.383)**	[3.250]
	[2.802]*		
$\widehat{\theta}_j \times \ln(Y)$	1.831		
	(0.478)***		
	[0.520]***		
$\widehat{\theta}_j^{nh} \times \ln(Y)$			5.434
			[1.901]***
Product-destination	Yes	Yes	Yes
Destination-date	Yes	Yes	Yes
Brand-year	Yes	Yes	Yes
Attributes $\times$ $\ln(Y)$	No	Yes	No
N	284,025	272,737	272,737

Notes: The dependent variable is the logarithm of the market share of product j, at date t and destination country i. The log of price is instrumented with the third lag of the exchange rate. The estimation follows the estimation approach in Column (5) of Table 3. The table reports the results from the estimation of eq. (13), and the two steps involved in the estimation of eq. (14) shown separately in Columns (2) and (3). In Column (1), the log of income, $\ln(Y)$, is interacted with the homothetic inferred quality measure used in Section 3. Robust standard errors clustered by country are reported in parentheses. Brackets report bootstrapped standard errors based on 500 replications and resampling by country. In both specifications, all stages involved in the estimation are bootstrapped. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

throughout Section 3. In particular, those preferences seem to be missing some degree of heterogeneity in the response of market shares (conditional on prices) at different income levels, which is now being captured by the interaction term $\theta_j \times \ln Y_{i,t}$.

4.2 Inferring Quality under Nonhomothetic Preferences

Provided that preferences are indeed nonhomothetic, $\widehat{\theta}_j$ would be derived from an inaccurate specification of consumer behavior. Specifically, if preferences are represented by (9) and (12), then income effects captured by the interaction term $\theta_j \times \ln(Y_{i,t})$ must be taken into account when inferring model j's quality from quantitative market shares. The specifications reported in Columns (2) and (3) of Table 6 aim at achieving this objective. We do so in two separate steps, each one reported in one of those two columns. We first let θ_j be determined by the set of main attributes displayed in Table 5, plus an additional unobserved component. That is, we let

$$\theta_j = \sum\nolimits_{k=1}^{9} \alpha_c \cdot z_{c,j} + \vartheta_j, \tag{14}$$

where each $z_{c,j}$ summarises attribute c in model j and ϑ_j captures any other unobserved determinants of quality.

Based on equation (14), we could re-write equation (13) as follows:

$$\ln m_{i,j,t} = -\sigma \, \ln p_{i,j,t} + \sum\nolimits_{c=1}^{9} \tau_c \cdot (z_{c,j} \times \ln Y_{i,t}) + \widetilde{\mu}_{i,t} + \widetilde{\phi}_{i,j} + \widetilde{\upsilon}_{i,j,t}, \tag{15}$$

where $\tau_c \equiv \kappa \cdot \alpha_c$.[32] Compared to (13), equation (15) includes a set of nine interaction terms between models' attributes ($z_{c,j}$) and log-income per head, which act as "stand-in" for θ_j in (13).

Column (2) of Table 6 displays the estimated $\widehat{\sigma}$ based on a 2SLS estimation of (15).[33] Unlike Table 3, the price elasticity is now estimated in a specification that allows for the impact of the nonhomothetic term $\theta_j \times \ln Y_{i,t}$. However, given that the parameters τ_c are each the result of a product $(\kappa \cdot \alpha_c)$, the estimates $\widehat{\tau}_c$ are not able to identify κ and each α_c separately. Thus, to obtain an estimated value of κ in this context, in a second step we rely on the estimates in Column (2) of Table 6 to compute inferred quality measures that accommodate nonhomothetic behavior by consumers, averaging across i

[32] Note that the error term $\widetilde{\upsilon}_{i,j,t}$ includes the period-specific deviations of the interaction term between the unobserved quality component ϑ_j and $\ln Y_{i,t}$.

[33] Relative to the point estimate in Table 3, the price elasticity in Table 6 rises slightly. A downward bias in the magnitude of the price elasticity under the assumption of homothetic preferences could be the consequence of income-dependent mark-ups. More precisely, if mark-ups on higher-quality varieties tend to be higher in richer countries, then *not* properly accounting for the impact of nonhomothetic preferences along the quality dimension could lead to a downwards bias in the estimated price elasticity.

and t analogously to eq. (6). Namely,

$$\widehat{\theta}_j^{nh} = \frac{\sum_{i\in\mathcal{I}}\sum_{t\in\mathcal{T}} \ln m_{i,j,t} - \left(-\widehat{\sigma}^{nh}\ln p_{i,j,t} + \widehat{\mu}_{i,t}^{nh}\right)}{N\times T} \tag{16}$$

Column (3) reports results from the estimation of (13) where θ_j is now measured by $\widehat{\theta}_j^{nh}$ obtained from (16). The main advantage of using $\widehat{\theta}_j^{nh}$ is that it is no longer necessary to rely on residual market shares obtained from the homothetic log-market shares regression equation (4). As long as the term $\sum_{c=1}^{9}\alpha_c\cdot z_{c,j}$ manages to capture a substantial amount of variation in intrinsic quality across models, income effects would be reflected in the residual market shares.[34] As before, due to the use of generated regressors, all three stages of this estimation are jointly bootstrapped for the purposes of statistical inference.[35]

Compared to Column (1), the estimate of κ in Column (3) increases substantially and remains positive and statistically significant at 1%. The near tripling of the point estimate indicates that when preferences are assumed to be homothetic, the income elasticity of quality is likely underestimated. (Recall that the interaction term estimates in Table 6 are directly comparable in terms of magnitude, since the different inferred quality measures used in the regressions have all been standardized.) One possible explanation for a downward bias could be measurement error in inferred quality $\widehat{\theta}_j$ stemming from misspecified preferences.[36]

[34] An alternative approach would be to directly subtract the price effect from the (log) market shares by means of the estimated $\widehat{\sigma}$ in Column (2). That is, we could use $\ln m_{i,j,t} + \widehat{\sigma}\ln p_{i,j,t}$ as the dependent variable of an OLS regression where $\widehat{\sigma} = 5.533$.

[35] Columns (2) and (3) of Table A.4 in the Appendix reproduce the specifications in columns (2) and (3) of Table 6 augmented with market age-by-country controls, $mage_{y,i}$. The coefficient on the interaction term between the estimated non-homothetic inferred quality measure and income remains statistically and economically meaningful. Similarly to the outcome of the same robustness check in the homothetic case, the price elasticity estimate exhibits a small decline.

[36] One possible concern with our estimates of inferred quality is to do with selection and heterogeneous intensity of competition faced by different models. Such heterogeneity may arise due to varying market composition, as a product's relative position within a quality distribution would be country-specific. A positive association between income and the stringency of energy-related legislation, for example, could lead to a regulation-induced narrowing of the quality gap in high income countries, which intensifies competition. To address this concern, Table A.5 re-runs the regressions shown in Table 6 restricting the sample to products that face a sufficiently diverse set of competitors, where the degree of diversity is measured by the coefficient of variation of the energy efficiency rating in the market in a given period. The results of this exercise are reported in Table A.5 and remain similar to those in Table 6 indicating that endogenous competition/energy regulations are unlikely to bias the quality estimates.

4.3 Quality Measures Comparison: Homothetic vs. Nonhomothetic Preferences

The previous results strongly reject homothetic preferences. This, in turn, means that the quality measures inferred under the homothetic framework will fail to account for the heterogeneous impact of income at different layers of quality. Two important questions that follow are then: i) How different are the quality measures based on homothetic CES utility relative to those based on the nonhomothetic CES utility?; ii) What attributes tend to drive a wedge between those two quality measures? In what follows, we briefly address these two issues.

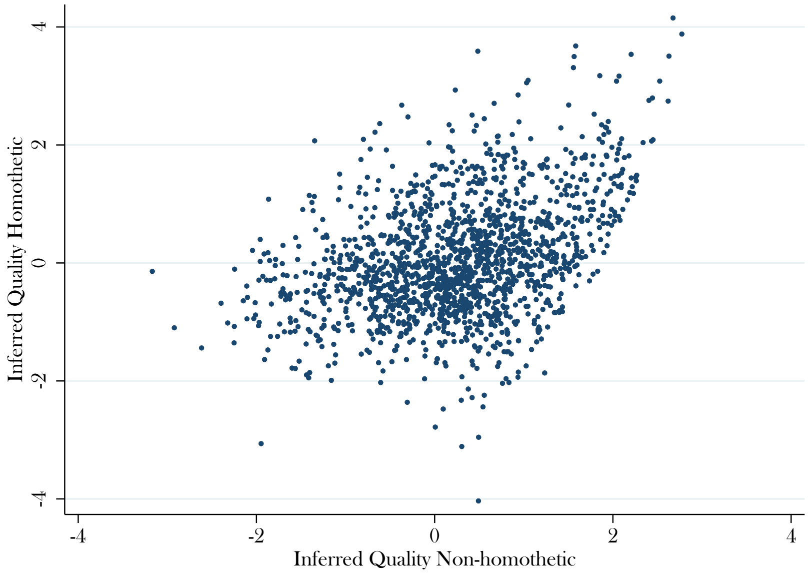
Regarding the first question, Figure 2 displays a scatter plot of the quality measures inferred under nonhomothetic CES utility (on the horizontal axis) and those based on homothetic CES utility (on the vertical axis). Despite being clearly positive, the correlation between the two measures is moderate – approximately equal to 0.4. In fact, we can observe that for a substantive number of models, significant disparities arise between the two quality measures. Furthermore, from an ordinal perspective, accounting for nonhomotheticities leads not only to changes in the intensity of preferences for different fridge models, but also to reshuffling in quality rankings, which suggests that the relative importance of different attributes on quality may change when income effects via nonhomothetic preferences are taken into consideration.[37]

This expectation is confirmed in Table A.3 in Appendix A.1.2, which compares the parameter estimates of different attributes on the inferred quality measures in the case of homothetic and nonhomothetic preferences.[38] The most striking result in Table A.3 is the substantial rise in the importance of energy efficiency as a determinant of quality. The magnitude of the coefficients associated with each label increases substantially in Column (3) relative to Column (2). The change in the contribution of energy efficiency to quality is paired with some other attributes experiencing a reduction in their impact. The fact that attributes like 'dispenser' and 'display', which do contribute to the final price of a fridge–as reflected in Column (6) in Table 5– turn insignificant suggests that homothetic preferences end up confounding a substantial amount of variation in prices with variation in quality, at least relative to a nonhomothetic preference specification.

[37] If fridge models could be cleanly ex-ante ordered by virtue of their vertical attributes, one would not expect to see much rank reshuffling. (Of course, even in that case, the correlation between quality measures could be far from one.) Despite its potential appeal, an ex-ante quality ranking would be virtually impossible to carry out in the data set without imposing arbitrary assumptions on attributes' weights on quality. For example, there are models with A+++ energy rating but that lack a zero-degree box and do not contain a no-frost system, while other models with lower energy efficiency comprise those two features. In general, overlapping patterns across vertically ordered attributes are ubiquitous and the rule in the data, rather than the exception.

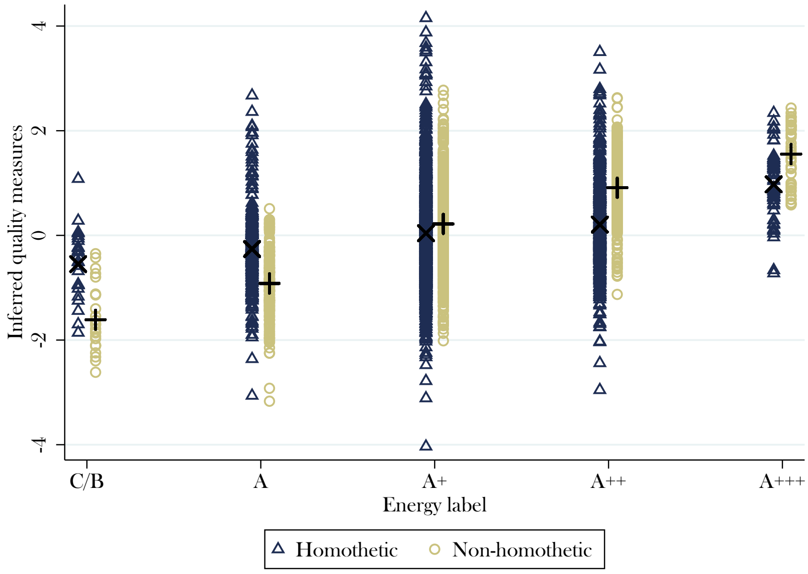
[38] Note that the estimates are directly comparable since quality measures are standardized.

Figure 2 – Quality Measures Correlation



Notes: The scatterplot correlates the quality measures under homothetic and nonhomothetic preferences for each of the models in the sample.

Figure 3 – Quality Measures and Energy Efficiency



Notes: Each triangle represents a fridge model and its quality measured under homothetic preferences. Each circle represents a fridge model and its quality measured under nonhomothetic preferences. The X's (resp. +'s) pinpoint the average quality of models at each level of energy efficiency under homothetic preferences (resp. nonhomothetic preferences).

Figure 3 provides a visual description of how the importance of energy efficiency for quality varies when accounting for nonhomotheticicities. The horizontal axis orders the fridges by their energy efficiency label, while the vertical axis measures their quality based on the two alternative preference specifications. The figure shows that for low energy efficiency models B/C and A, the distribution of homothetic quality measures first-order stochastically dominates that of the nonhomothetic quality measures. Conversely, for energy classes A++ and A+++, the opposite occurs: high energy efficiency models tend to receive a higher quality rating under the nonhomothetic CES than under homothetic CES. An important message from Figure 3 is that being able to produce greener fridges with high energy efficiency may be crucial for attracting richer consumers. Not controlling for the variation in the appeal that greener fridges enjoy at higher levels of income may lead to a misleading picture of the types of attributes that are most valued in richer markets and the factors that maximize market penetration. Furthermore, the implications of this result potentially extend beyond the refrigerator industry: almost all household appliances in the EU are subject to analogous labeling requirements.

5 Supply-Side Analysis: Choice of Production Location

This section explores the production location choices for varieties in a setting with multi-plant producers. The main goal is to check if firms' location decisions vary with the quality level of a given variety. In particular, we investigate whether there exists a connection between a refrigerator's intrinsic quality and the per-capita income of the country hosting its production, and if such a connection is suggestive of the presence of a "home-market" effect.

The home-market effect relies on a demand-side argument: in the presence of geographic barriers and economies of scale, firms may seek to manufacture a product in countries where local demand for it is greater.[39] The analysis in Section 4 reveals that demand for higher-quality refrigerators tends to be stronger in richer countries. Firms may then optimally choose to locate the production of specific models in countries where their quality best matches the domestic households' (income-dependent) preferences. Given the findings in Section 4, we expect a positive association between a model's quality and the level of per-capita income in its country of origin.

Alongside the home-market effect, production location choices may also respond to traditional comparative advantage considerations stemming from (exogenous) differences in technologies or factor endowments. Specifically with regard to quality differentiation, it can be argued that manufacturing more sophisticated models requires an environment

[39] This argument echoes the Linder (1961) hypothesis, according to which a requirement for profitably exporting a product is that there exists a strong domestic demand for it.

featuring higher levels of human capital and easier access to financial markets.

Section 5.1 develops a stilyzed framework to illustrate the emergence of a home-market effect, and explores the influence of cross-country productivity differentials on firms' decision making. We use the resulting theoretical predictions to guide a series of empirical and quantitative exercises, whose findings are reported in Section 5.2 and 5.3, respectively. The mathematical derivation of the expressions in the entire section are shown in Appendix A.1.1.3.

5.1 Optimal Location Choice with a Home-Market Effect

Consider a profit-maximizing firm that is facing the decision of where to locate the production line for a generic fridge model j. Let model j be characterized by a level of intrinsic quality θ_j. To keep the analysis brief and simplify notation, we consider a one-period framework, drop time and sector subscripts from the demand function (A.36) in Appendix A.1.1.2, and assume that the demand shifters $\lambda_{i,j}$ in (A.36) do not vary at the destination country level: formally, $\lambda_{i,j} = \lambda_j$. In addition, we consider the simplest case where the firm can locate the production model j in either of two countries, h and l. To abstract from effects stemming from relative population differences, we assume that both h and l have identical population, normalized to one.[40] Finally, throughout this subsection, we refer to the quality level of model j as the monotonic transformation $\lambda_j = \exp(\theta_j)$.[41] Under these assumptions, the demand function for model j in country i becomes:

$$q_{i,j} = \Omega_i \lambda_j p_{i,j}^{-\sigma} Y_i^{\tilde{\kappa}(\lambda_j)}, \tag{17}$$

where $\tilde{\kappa}(\lambda_j) \equiv \kappa \cdot \ln \lambda_j$, and $\Omega_i \equiv \alpha P_i^{\sigma} \left(\sum_{j' \in \mathcal{J}} \lambda_{j'} e^{\frac{1}{\sigma}} Y_i^{\frac{\tilde{\kappa}\left(\lambda_{j'}\right)-\sigma}{\sigma}} q_{i,j'}^{\frac{\sigma-1}{\sigma}} \right)^{-\sigma}$.

Henceforth, we refer to generic countries of origin and destination with the letters k and i, respectively. If model j ends up being produced in country $k = h, l$, households from $i \neq k$ need to import it from k. We assume that shipping goods across countries entails an iceberg cost $\tau > 1$. Let $\tau_{k,i}$ be an indicator function equal to τ when $i \neq k$ and 1 when $i = k$. Then, given the demand function (17), the price that the firm optimally charges in country i when model j is produced in country k is:

$$p_{i,j}^{k} = \tau_{k,i} c_{k,j} \sigma / (\sigma - 1), \tag{18}$$

[40]This simplifying assumption could be dispensed with, albeit at the cost of substantially heavier algebraic expressions. In particular, allowing for population differences between h and l will not invalidate any of our main results but, as we will see in Section 5.3 below, actually reinforce the strength of comparative advantage across the quality dimension stemming from the home-market effect.

[41]We revert back to $\theta_j = \ln(\lambda_j)$ in the empirical analysis that follows.

where $c_{k,j}$ is the marginal cost of model j. It follows that the profit obtained in i when j is produced in k reads:

$$\Pi_{i,j}^{k} = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \frac{\Omega_i \lambda_j Y_i^{\tilde{\kappa}(\lambda_j)}}{(\tau_{k,i} c_{k,j})^{\sigma-1}}, \tag{19}$$

where $Y_i > 0$ is real income. Henceforth, without any loss of generality, we let $Y_h/Y_l \equiv Y > 1$.

Recalling that population is assumed to be identical in h and l (and normalized to one), total profit earned by the firm when model j is produced in country $k = h, l$, denoted by $\Pi_j^k \equiv \Pi_{h,j}^k + \Pi_{l,j}^k$, is thus given by:

$$\Pi_j^k = \frac{(\sigma-1)^{\sigma-1}}{\sigma^{\sigma}} \frac{\lambda_j}{c_{k,j}^{\sigma-1}} \left[\frac{\Omega_h Y_h^{\tilde{\kappa}(\lambda_j)}}{\tau_{k,h}^{\sigma-1}} + \frac{\Omega_l Y_l^{\tilde{\kappa}(\lambda_j)}}{\tau_{k,l}^{\sigma-1}} \right]. \tag{20}$$

We can compare the firm's profit when model j is produced in h relative to that when produced in l by computing the profit ratio:

$$\varpi_j \equiv \frac{\Pi_j^h}{\Pi_j^l} = \left(\frac{c_{l,j}}{c_{h,j}} \right)^{\sigma-1} \Upsilon(\lambda_j), \tag{21}$$

where $\Upsilon(\lambda_j) \equiv \left[1 + \tau^{\sigma-1} \Omega Y^{\tilde{\kappa}(\lambda_j)}\right] / \left[\tau^{\sigma-1} + \Omega Y^{\tilde{\kappa}(\lambda_j)}\right]$, with $\Omega \equiv \Omega_h/\Omega_l$, captures the role played by the cross-country income differentials in determining whether it is more profitable to locate production in h or l. Given that $\tau \geq 1$, clearly $\Upsilon'(\lambda_j) > 0$. This indicates that the higher the quality level of model j, the greater the extent to which income disparities matter to cross-country profit differentials.

We can now formalize the resulting relationship between the profit ratio ϖ_j and the model j's quality level λ_j, for given values of the marginal costs $c_{l,j}$ and $c_{h,j}$.

Lemma 1 (Home-market effect) *Holding the marginal cost ratio $c_{l,j}/c_{h,j}$ fixed, the profit ratio ϖ_j is increasing in λ_j.*

Lemma 1 states that, in the presence of nonhomotheticicities along the quality dimension, profits obtained by producing a certain fridge model in the richer country (relative to producing it in the poorer country) are increasing in the model's intrinsic quality. This result rests on the interplay between the iceberg transport cost τ and the higher willingness-to-pay for quality by country h, and constitutes the key mechanism leading to a home-market effect.

In order to account for other factors potentially influencing specialization, we next explicitly model the technologies available to the firm. Let country k be characterised by a real wage $\omega_k > 0$, which is assumed to be determined exogenously, and is such that $\omega_h/\omega_l \equiv \omega > 1$. We borrow the production structure from Eaton and Kortum (2002), and assume that $c_{k,j} = \omega_k/\zeta_{k,j}$ where $\zeta_{k,j}$ measures labor productivity in terms of model j in country k. Each $\zeta_{k,j}$ is drawn from a Fréchet distribution with location parameter $T_{k,j}$ and shape parameter equal to δ, namely:

$$F_{k,j}(\zeta) = \exp\left(-T_{k,j}^{\delta}\zeta^{-\delta}\right). \tag{22}$$

To give some structure to the location parameter, we let $T_{k,j} \equiv A_k^{\alpha}\left(1+\xi\lambda_j\right)^{-(1+\psi/A_k)}$, with $\psi \geq 0$ and $\alpha, \xi > 0$. A_k can be interpreted as a "stand-in" for a number of factor endowments specific to country k, such as human capital availability, with α governing how a larger A_k leads to higher aggregate labor productivity. The parameter ψ determines whether A_k generates a comparative advantage in higher quality varieties (the larger the value of ψ, the stronger the relative effect of A_k for higher-quality varieties). The parameter ξ in turn governs how quality upgrading translates into greater unit labor requirements.

Henceforth, we assume that $A_h > A_l$ to reflect the fact that the factor endowments tend to be positively correlated with income per head across countries. The formal definition of $T_{k,j}$ aims at capturing three specific features of technologies. First, fridges of higher-quality have larger labor unit requirements ($\partial T_{k,j}/\partial\lambda_j < 0$). Second, for any given model j, a larger A_k leads to smaller labor unit requirements ($\partial T_{k,j}/\partial A_k > 0$). Third, larger endowments increase productivity relatively more for higher quality varieties ($\partial^2 T_{k,j}/\left(\partial A_k \partial\lambda_j\right) \geq 0$, with strict inequality whenever $\psi > 0$.

Using $c_{k,j} = \omega_k/\zeta_{k,j}$ jointly with (21) yields:

$$\varpi_j > 1 \quad \Leftrightarrow \quad \zeta_{h,j} > \zeta_{l,j}\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega. \tag{23}$$

Combining (23) with (22) gives the probability that model j is produced in country h:

$$\Pr_j^h = \frac{1}{1+\left[\left(\frac{A_l}{A_h}\right)^{\alpha}\left(1+\xi\lambda_j\right)^{\frac{\psi}{A_h}-\frac{\psi}{A_l}}\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega\right]^{\delta}}. \tag{24}$$

This expression indicates that cross-country differentials in A_k may give rise to heterogeneous responses of $\Pr_j^h$ as λ_j varies. The following proposition formally illustrates this point.

Proposition 1 (Patterns of quality specialization) *The patterns of quality specializa-*

tion between h and l are determined by a home-market effect and a local factor-endowment effect. In particular:

1. *If $\psi = 0$, quality specialization is solely driven by the home-market effect linked to nonhomothetic preferences: the probability that a given model j is produced in the richer country is increasing in λ_j.*
2. *If $\psi > 0$, both the home-market effect and the local factor-endowment effect lead to a higher probability that a given model j is produced in country h as λ_j increases.*

Proposition 1 shows that, apart from the home-market effect, heterogeneous country-specific factor endowments may also impact quality specialization. In the following subsection, we empirically assess the relative importance of these two factors. As we will see, the results suggest that quality specialization in the fridge industry appears to be primarily driven by the presence of a home-market effect.

5.2 Quality and Production Location: Empirical Analysis

We now bring the predictions resulting from the two mechanisms discussed above to the data. The empirical analysis is grounded on a regression equation featuring the level of inferred quality $\widehat{\theta}_j^{nh}$ derived in Section 4 as a dependent variable. As regressors, we include log-income per capita of country k where model j is produced, $y_{k,j} \equiv \ln(Y_{k,j})$, as well as a number of local supply-side factors, whose impact on specialization in our model is captured by the variable $A_{k,j}$.[42] In particular, for the country of origin k of each model j, we consider an index of human capital and an indicator of financial market accessibility. Notice that as each model is produced in a single location throughout its whole market life, we can abstract from the time dimension of the panel data. Given the observed life-cycle of model j measured from the first to the last year j is supplied to any destination country in the data, $y_{k,j} \equiv \ln(Y_{k,j})$ and $A_{k,j}$ are country-of-origin and model-specific time averages over the life-cycle of the product.[43]

Formally, we consider the following specification:

$$\widehat{\theta}_j^{nh} = \gamma\, y_{k,j} + \eta\, A_{k,j} + \varepsilon_j, \tag{25}$$

where γ and η are the main parameters of interest. Following the above discussion, the presence of a home-market effect would imply that $\gamma > 0$.

[42] Table A.10 in the Online Appendix reports the countries of origin involved in the analysis, listed by brand.

[43] All results are robust to using values of the explanatory variables at the date when model j is first observed in the data. These results are available from the authors upon request.

Table 7 reports coefficient estimates for a number of different specifications of equation (25), each one varying in terms of the country-of-origin-specific variable represented by $A_{k,j}$. We proceed to include only one supply-side variable at a time, given the strong joint correlation between them. Column (1) presents results based on log-GDP per capita as a single regressor. This specification intends to capture the association between income and the production location choice across models differing in quality as suggested by Lemma 1, disregarding other factors that may influence relative productivity in higher-quality models. The estimated value of γ is positive and statistically significant, suggesting that richer countries tend to attract the production of higher-quality fridges, which is, in principle, consistent with the presence of a home-market effect.

The simple correlation between log-income per capita and product quality displayed in Column (1) could be merely capturing a link between quality specialization and other local factors that are in turn correlated with income, as posited by case 2 of Proposition 1. In Columns (2) and (3), we sequentially add measures of some of these factors to assess their association with quality specialization, and check whether the magnitude and significance of the income-per-capita effect change. Column (2) adds the (log) human capital index to control for the relative availability of skilled labor. It might be argued that more sophisticated models require higher-skilled labor to be efficiently manufactured.[44] The coefficient of the human capital index is not significantly different from zero, while the effect of per-capita GDP decreases, but retains significance at 10%. This evidence is suggestive of a relevant role of local income in determining quality specialization, even if one accounts for its correlation with skill abundance.

Column (3) incorporates a measure of financial development. Different degrees of financial imperfections across countries may heterogeneously influence the production costs of models of different quality. More generally, it may be the case that higher-quality varieties of fridges are relatively more dependent on the availability of external finance (for example, if they require higher initial outlays of R&D investment). The results show that access to financial markets appears to play an important role in influencing quality specialization. In any case, the point estimate of log-income per head remains positive and significant.

Next, we include the logarithm of total GDP as a proxy for overall market size to account for the possibility that scale effects might drive firms' location choices by being stronger for higher quality goods. Column (4) shows that including a measure of market size to control for heterogeneous scale effects along the quality dimension does not alter our

[44] For evidence linking labor skills to product quality in manufacturing, see, e.g., Verhoogen (2008); Brambilla, Lederman and Porto (2012); Fieler, Eslava and Xu (2018); and Bastos, Silva and Verhoogen (2018).

Table 7 – Quality and Production Location

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:				$\widehat{\theta}_j^{nh}$				
log(GDP p.c.)	0.598	0.484	0.521	0.559	0.427	0.416	0.437	0.365
	(0.202)***	(0.260)*	(0.161)***	(0.182)***	(0.157)**	(0.253)	(0.160)**	(0.141)**
Human Capital Index		0.010				-0.011		
		(0.260)				(0.311)		
log(Fin. Dev. Index)			0.138				0.010	
			(0.034)***				(0.065)	
log(GDP)				0.045				0.073
				(0.065)				(0.057)
Brand FE	No	No	No	No	Yes	Yes	Yes	Yes
N	2,069	1,983	2,068	2,069	2,068	1,982	2,067	2,068
R^2	0.072	0.049	0.095	0.076	0.281	0.239	0.286	0.286

Notes: The table shows results from OLS estimation of eq. (25) in which the dependent variable is the inferred quality measure defined by eq. (16). The regressors, which refer to the country where models are produced, are time averages over the observed life cycle of each model, which is measured from the first to the last year the model is supplied to any destination country in the data. GDP, human capital index, and population (used for the computation of per-capita GDP) are retrieved from the Penn World Tables. The financial development index is retrieved from the World Bank Database, using private credit over GDP. Robust standard errors two-way clustered at the level of brand and country of origin are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

earlier findings.[45]

The previous results are based on variation in location choices regardless of the specific firm that produces each fridge model. In Columns (5)-(8), we reassess the impact of income per head on quality specialization by exploiting variation only within brands, via the inclusion of brand fixed effects. This set of dummies controls for the possibility that brands differ in terms of their average quality of production, and they ex-ante choose specific locations with certain levels of income per head accordingly. A comparison with the previous four columns indicates that our results remain qualitatively intact, with the exception of the estimated coefficient on average log-GDP per head in Column (6), whose p-value marginally exceeds 10%. The estimates slightly decrease in magnitude after controlling for brand fixed effects, consistent with the idea that brands producing (on average) higher-quality models tend to locate their plants in richer countries. However, and most importantly, the association between income per head and quality generally remains positive and significant.

This finding suggests that the home-market effect is still present even if we only exploit variation in location choices within firms. In other words, the home-market effect driving quality specialization across countries appears to be strong enough such that it holds even when considering location choices *within* multi-product firms, which tend to allocate the production of higher-quality models in their plants located in richer countries.[46]

One concern with the results reported in Table 7 is whether variations in log-GDP per head actually help in identifying the impact of consumers' income on production location choices. It could be argued that even after controlling for several local supply-side factors and even when restricting the analysis to location choices for different models within the same brands, per-capita income variations might still be reflecting other possibly unobservable sources of productivity differences across countries influencing quality specialization. To alleviate this concern, we replicate the estimation replacing log-GDP per capita with an adaptation of the two versions of market access measures proposed by

[45] To assess the robustness of the impact of income per head on quality specialization to other possible omitted factors, Table A.6 in the Appendix reports specifications that incorporate the logs of physical capital, population, land area and a weighted average distance from the country of origin to all possible destinations, as well as a rule of law index. Note that if, for whatever reason, remote countries of origin relative to destinations have high income per capita, and ship their highest quality products to faraway destinations, then omitting distance from the estimation will lead to inconsistent and biased results. The table shows that the coefficient on the log-GDP per capita remains positive and statistically significant in all specifications.

[46] It is worth noting that, as Column (7) shows, the inclusion of brand fixed effects renders the point estimate of the log of financial development insignificant. This might indicate that, while important across firms, difficulties in obtaining local access to credit may be mitigated within firms, possibly using financial resources obtained in a centralized fashion (e.g., in the country where the headquarters are located).

Table 8 – Quality and Market Access of Production Locations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:						$\widehat{\theta}_j^{nh}$				
Market Access (M^1)	1.240	1.592	1.346	1.186	1.887					
	(0.229)***	(0.656)**	(0.315)***	(0.231)***	(0.693)**					
Human Capital Index		-0.436					-0.365			
		(0.473)					(0.348)			
log(Fin. Dev. Index)			-0.077					-0.067		
			(0.079)					(0.072)		
log(GDP)				0.070					0.127	
				(0.093)					(0.097)	
log(GDP)p.c.					-0.486					-0.185
					(0.384)					(0.224)
Market Access (M^2)						1.609	1.881	1.682	1.645	1.823
						(0.377)***	(0.648)***	(0.445)***	(0.250)***	(0.563)***
Brand FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,068	1,982	2,067	2,068	2,068	2,068	1,982	2,067	2,068	2,068
R^2	0.325	0.293	0.332	0.330	0.335	0.347	0.314	0.351	0.363	0.350

Notes: The table shows results from OLS estimation of eq. (25) in which the dependent variable is the inferred quality measure defined by eq. (16). The regressors, which refer to the country where models are produced, are time averages over the observed life cycle of each model, which is measured from the first to the last year the model is supplied to any destination country in the data. The market access measures, M^1 and M^2, are defined by eq. (26). GDP, human capital index, and population (used for the computation of per-capita GDP) are retrieved from the Penn World Tables. The financial development index is retrieved from the World Bank Database using private credit over GDP. Bilateral distances are retrieved from the CEPII dataset, using intra-country agglomeration weighted measures. Robust standard errors two-way clustered at the level of brand and country of origin are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dingel (2017) to an international trade context.

The market access measures are based on gravity considerations and aim to reflect the income structure of potential consumers. Formally, they are defined by:

$$M^1_{k,j} = \sum\nolimits_i \frac{N_i dist_{i,k}^{-d}}{\sum_{i'} N_{i'} dist_{i',k}^{-d}} y_i, \quad M^2_{k,j} = \sum\nolimits_{i \neq k} \frac{N_i dist_{i,k}^{-d}}{\sum_{i' \neq k} N_{i'} dist_{i',k}^{-d}} y_i, \tag{26}$$

where N_i and y_i respectively denote the population and the log-GDP per head of the country of destination i, $dist_{i,k}$ the bilateral distance between i and k weighted by intra-country agglomeration measures, and d the distance elasticity of trade volumes.[47] The two measures differ in that $M^2_{k,j}$ excludes the income per head of country k where model j is produced. As a consequence, it fully avoids confounding local supply-side factors with demand-side ones. The results of the ensuing regressions, reported in Table 8, confirm our findings.[48] Importantly, they also show that the coefficients on the variables capturing the home-market effect are positive and significant even in the presence of the human capital index as an additional regressor.[49]

When combined with the evidence on nonhomothetic preference along the quality dimension presented in Section 4, the results in Tables 7 and 8 point to the presence of a strong home-market effect as a key determinant of firms' production location choices. Furthermore, the home-market effect holds not only across brands but also within brands. The supporting evidence of a home-market effect is in line with Dingel (2017), albeit in a different context. Based on microdata on U.S. manufacturing plants across U.S. cities, Dingel (2017) demonstrates that the home-market effect plays a quantitatively more prominent role in explaining quality specialization across U.S. cities than differences in relative factor abundance. We show that similar results arise when looking at quality specialization across different countries and even within the same firms.

[47] We estimate the value $d = 1.44$ using a gravity model applied to bilateral trade flows in the HS6 category 841810 ('combined refrigerator-freezers, fitted with separate external doors'). The relevant estimation results are available from the authors upon request.

[48] Table 8 features two additional columns relative to Table 7, specifically, Columns (5) and (10), in which we include the log-GDP per head as an additional regressor to control for potential spatial correlation in per capita income.

[49] As further robustness checks, we repeat the analyses in Tables 7-8 using parent fixed effects in place of brand fixed effects (e.g. BSH GmbH is the parent of the brands Bosch, Siemens, and Gaggenau), including a measure of environmental stringency at the country level as an additional covariate to control for the possibility of a confounding effect through the positive correlation between environmental regulation stringency and income per capita, and adding a dummy for the models produced in the country hosting the producer's headquarters to check whether those models turn out to be the main driver of the home-bias estimates. The results of these additional specifications are in line with those in Tables 7-8 and are available from the authors upon request.

One final consideration is whether there are specific features of the refrigerators industry that may help explain the particular strength of the home-market effect as a force influencing location choices. Refrigerators are final goods that are relatively costly to transport across long distances, especially when comparing that to transporting several of their intermediate inputs and components that tend to be sourced from global value chains (see, e.g., Sit, 2015). To some extent, one could expect that final output location choices are essentially final assembly location choices. Indeed, the global value chain (GVC) literature shows that the "Household refrigerators and freezers" category is associated with a relatively low value of "upstreamness" (lying in the second decile of the ranking of all product sectors in the IO2002 nomenclature according to Alfaro, Antràs, Chor and Conconi (2019)) and a relatively high value of "downstreamness" (lying in the ninth decile according to Antràs and Chor (2018)). This indicates that the manufacturing activities in the refrigerators sector are relatively assembly-intensive. In a context with GVC, it is arguably for assembly-intensive industries that one would expect to see large scope for home-market considerations when choosing the production location of quality-differentiated goods. Furthermore, the results in this section are also in line with anecdotal evidence of relatively high mobility of skilled workers within companies in the refrigerators sector, which points to a less pressing need to locate the production of higher-quality goods where skilled labor is more abundant.[50]

5.3 Quality and Production Location: Counterfactual Analysis

In an attempt to provide a structural link between the data and the model developed in Section 5.1, this subsection gauges the relative importance of the home market effect vis-a-vis the impact of the endowment effect through a quantitative counterfactual exercise. Given that our theoretical framework considers a single manufacturer and two production locations, we structure the following analysis as a case study on a single brand. In particular, we focus on Liebherr because it features the highest number of refrigerator models with only three production locations, namely: Austria, Bulgaria, and Germany.[51] To avoid arbitrary choices in averaging the variables involved across countries, we use only models produced in two out of three production locations. We let Germany represent country h and Bulgaria country l, given that these countries host the production of most models (238 and 154, respectively), and disregard Austria (47).[52]

[50] See, e.g., Sit (2015), who reports on the case of the manufacture of refrigerators by a Japanese conglomerate in Thailand featuring 30 Japanese engineers, among nearly 5000 employees.

[51] Our data set contains 439 models produced by Liebherr, more than twice as many as Electrolux (the second most important brand in terms of number of models).

[52] Similar results obtain by merging Austria and Germany due to the more similar level of development relative to Bulgaria in the role of country h. The results are available from the authors upon request.

In Section 5.1, the equilibrium distribution of models by location is summarized by eq. (24), which comprises several different parameters and equilibrium objects. Some of these elements are drawn directly from estimations in Section 4. Specifically, the models' quality levels $\lambda_j \equiv \exp(\theta_j)$ obtain by using $\hat{\theta}_j^{nh}$ calculated from (16) as a measure for θ_j. The price elasticity σ and the income elasticity of quality κ are set equal to the respective estimates reported in Columns (2) and (3) of Table 6. The remaining objects are matched to their observed counterparts. The factor endowment A_i is the human capital index in country i; Real income Y_i is country i's per capita GDP. The relative wage ω is set equal to the relative real income (country h to l), and the transportation cost is $\tau = 1.05$.[53] To compute Ω_i, we let P_i be the consumer price index in country i. We also adjust Ω_i's magnitude to account for the size (population) of country i.

We need to identify the values of four additional structural parameters, namely: α, ξ, ψ, and δ. We do so in two steps. In the first step, we rely on the structure of the model to derive a regression equation linking the (log) price of product j with the ratio between j's quality (λ_j) and the level of human capital of the country where j is manufactured. Relying on the fact that each model j is produced in one specific location k, we can obtain the following expression (all details of the derivation of (27) from the structure of the model are presented in Appendix A.1.1.3):

$$\ln p_{i,j(k),t} = b \cdot \left(\frac{\lambda_{j(k)}}{A_{k,t}} \right) + \Phi_{i,k,t} + \Delta_{i,j(k)} + \varepsilon_{i,j(k),t}, \tag{27}$$

where $\Phi_{i,k,t}$ is a set of origin-destination-time fixed effects, $\Delta_{i,j(k)}$ destination-model fixed effects, and $\varepsilon_{i,j(k),t}$ an error term.

In light of the existing evidence in the literature linking skilled labor to product quality (see footnote 44 for the relevant references,) we carry out the estimation of (27) using human capital as a measure of $A_{k,t}$. The estimate for b is drawn from Table A.7 in Appendix A.1.2. Note that the estimate cannot identify ξ and ψ separately. Hence, we calibrate the model using our estimate of b to identify these parameters alongside α and δ. We proceed as follows. We split the observed fridge models' quality distribution in N bins, indexed by $n = 1, 2, ..., N$, each containing the same number of models. Bins are ranked in an increasing models' quality order. Hence, the within-bin average quality, denoted by $\hat{\lambda}_n$, is such that $\hat{\lambda}_{n'} \leq \hat{\lambda}_{n''}$ for any $n' < n''$. For each bin n, we let $\mathcal{M}_n^k$ be the number of fridge models belonging to bin n produced in country k, and define $\Gamma_n^h \equiv \mathcal{M}_n^h / \left(\mathcal{M}_n^h + \mathcal{M}_n^l \right)$ as the *frequency* of bin-n models produced in country h. We

[53]UNCTAD statistics suggest that the incidence of freight costs are about 5% of the value of imports in the last three decades. Results are robust to sensitivity tests carried out on both ω and τ.

Table 9 – Model's Parametrization and Values

Parameter	Value (1)	Variable	Country h (2)	Country l (3)
κ	5.4340	A_k	3.6577	3.1157
σ	5.5330	P_k	0.9911	0.4618
		Y_k	45,531	16,806
ψ	0.0965			
ξ	9.9995			
α	6.3525			
δ	5.4603			

Notes: The table reports the values of parameters and exogenous variables used to simulate equation (28). The parameters σ and κ equal the coefficients reported in Columns (2) and (3) of Table 6. The remaining parameters are obtained via calibration of (28) using the procedure described in the text. A_k, P_k, and Y_k are the human capital index, the consumer price index, and per capita GDP in country k, respectively.

compute Γ_n^h for each bin n using the analogous formula to (24):

$$\Gamma_n^h = \left\{ 1 + \left[\left(\frac{A_l}{A_h} \right)^{\alpha} \left(1 + \frac{b}{\psi} \hat{\lambda}_n \right)^{\frac{\psi}{A_h} - \frac{\psi}{A_l}} \Upsilon \left(\hat{\lambda}_n \right)^{-\frac{1}{\sigma - 1}} \omega \right]^{\delta} \right\}^{-1}, \; n = 1, 2, ..., N, \tag{28}$$

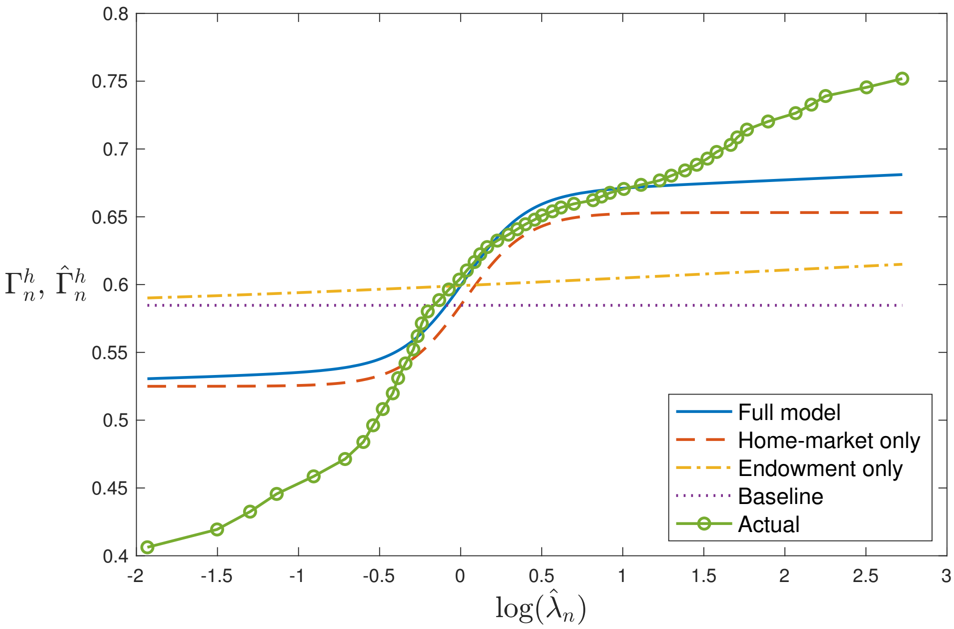
and interpret Γ_n^h as a "discretized" measure for $\Pr_j^h$.

We need three additional equations to $b = \xi \cdot \psi$ to produce and solve a (nonlinear) system in four unknowns, represented by the parameters α, ξ, ψ, and δ. Hence, we let $N = 3$ and use the observed frequency of bin-n models produced in country h, denoted by $\hat{\Gamma}_n^h$, as target for Γ_n^h. We solve the nonlinear equation system using a common root-finding software.[54] Table 9 reports the calibration's outcomes along with the estimated parameters and exogenous variables.

Figure 4 illustrates the counterfactual analysis' results. The line labelled 'Full model' portrays the completely characterized simulation of (28). The counterfactuals are generated as follows: 'Home-market only' is obtained by setting $\psi = 0$ (i.e., shutting down the impact of the endowment effect on quality specialization); 'Endowment only' by setting $\kappa = 0$ (i.e., shutting down the home-market effect); 'Baseline' by setting $\psi = 0$ and $\kappa = 0$ (i.e., shutting down both the endowment and home-market effects). We produce the line 'Actual' by repeating the binning procedure described above after setting $N = 50$. The resulting relationship between the observed $\hat{\Gamma}_n^h$ and $\hat{\lambda}_n$ is then interpolated using a

[54] Specifically, in order to avoid aberrant solutions that may arise due to the particular functional form of (28), we resort to the built-in MATLAB's `fmincon` function to solve the system of nonlinear equations, constraining all parameters to lie in the interval $(0, 10]$.

FIGURE 4 – COUNTERFACTUAL ANALYSIS



Notes: The figure illustrates the outcomes of the counterfactual analysis. The horizonal axis measures the within-bin average quality $\hat{\lambda}_n$. The vertical axis – the simulated frequency of within-bin models produced in country h (Germany), Γ_n^h, and its observed counterpart $\hat{\Gamma}_n^h$. The line labelled 'Full model' portrays the simulation of (28). In turn, 'Home-market only' is obtained by setting $\psi = 0$; 'Endowment only' – by setting $\kappa = 0$; 'Baseline' – by setting $\psi = 0$ and $\kappa = 0$. 'Actual' is produced through the binning procedure described in the text with $N = 50$, then interpolating the resulting relationship between the observed $\hat{\Gamma}_n^h$ and $\hat{\lambda}_n$ using a smoothing filter.

smoothing filter.[55]

The figure shows that the model performs fairly well in capturing the trend and shape of the relationship between the relative frequency of production in country h and the fridge model's quality. Most importantly, it suggests that the home-market effect is the main driver of quality specialization. This visual interpretation is confirmed by the model's fit decomposition, which we report in Table 10. The table compares the actual and simulated frequencies of models produced in country h for bins corresponding to different percentiles (first five rows), with the usual binning procedure and $N = 50$. The 'Full model' specification's fit oscillates between 85.6% and 99.4%, with an average of 95.4%. The 'Home-market' specification's fit oscillates between 87.9% and 98.6%, with an average of 94,4%. It does better than the 'Full model' specification at the 10th percentile. The reason is that the latter comprises both the home-market and the endowment effect, and the 'Endowment' specification's fit at the 10th percentile is particularly poor. Indeed, the 'Home-market' specification outperforms its 'Endowment' counterpart at all percentiles

[55]In particular, the graph uses the built-in MATLAB's `hpfilter` function, with smoothing parameter set to 20,000. A similar shape obtains with the `smooth` function, with span set to 40.

Table 10 – Model's Fit: A Comparison between $\hat{\Gamma}_n^h$ and Γ_n^h

Percentile	Data (1)	Full Model (2)	Home-market (3)	Endowment (4)
10	0.4713	0.5394	0.5282	0.5956
33	0.5964	0.5878	0.5735	0.5988
50	0.6408	0.6472	0.6316	0.6011
66	0.6649	0.6692	0.6513	0.6040
90	0.7143	0.6756	0.6531	0.6090
33↔66	0.0685	0.0814	0.0778	0.0052
10↔90	0.2429	0.1362	0.1249	0.0134

Notes: The table reports the outcomes of the counterfactual analysis. Each column reports the frequency of models produced in country h for bins representing different percentiles of the models' quality distribution. It also reports the frequency differentials for two pairs of bins. Column (1) reports the observed values $\hat{\Gamma}_n^h$. Columns (2)-(4) report the simulated values obtained with different versions of (28), respectively concerning the specifications 'Full model', 'Home-market only' ($\psi = 0$), and 'Endowment only' ($\kappa = 0$).

except the 33rd.

Table 10 also contrasts the frequency variation between the 33rd and 66th percentile, and between the 10th and 90th percentile. These values provide a more clear-cut performance measure as it emphasizes different specifications' ability to discern between low and high quality models in terms of production-site predictions. The average fit of the 'Home-market' specification is 68.9%, slightly better than the 'Full model' specification's (whose fit is 68.6%). The average 'Endowment' specification's fit is instead a mere 6.6%, acutely underperforming relative to the other specifications. We can then conclude that the counterfactual analysis supports the notion that the home-market effect is an important driver of quality specialization in the firm's choice of production location, in line with the empirical results described in the previous subsection.

6 Conclusion

This paper aims at inferring quality from consumer demand using model-level panel data on retail sales of refrigerators across EU markets. The granularity of the data allows us to look into several aspects associated with demand for quality and quality specialization, which have proven hard to tackle by previous efforts in the literature relying on customs data aggregated by product categories. In particular, we can test for the presence of nonhomotheticicities by exploting variation in market shares of the exact same fridge model across different EU markets. Building on this test, we propose a way to account for the impact of nonhomothetic demand when measuring quality. In addition, combining the panel data with data on the country of manufacture, we study patterns of quality specialization at the firm level.

The results cast strong support for the notion that demand for quality is nonhomothetic. After controlling for price differences, market shares of higher-quality fridge models tend to be greater in richer markets. This result adds to the evidence based on average unit values within product categories from customs data to proxy for quality. Unlike these studies, however, our results rely on comparing market shares of identical models across markets with different incomes. This allows us to elicit nonhomothetic demand schedules without possibly confounding the impact of income-dependent willingness-to-pay for quality with changes in average unit values resulting from changes in the composition of product bundles across destination markets.

The flexibility of our demand framework has allowed us to account for the impact of nonhomothetic demand when measuring quality, while simultaneously keeping the standard CES homothetic preference setup as a special case. Comparing results that account for nonhomothetic demand with those that do not, we show that some important discrepancies arise. One is to do with the magnitude of a parameter that in our setup captures how the demand income elasticities vary with quality. This parameter is underestimated when quality measures fail to properly reflect how preferences for quality change with income. Another is to do with how strongly the relative appeal of different attributes responds to income. In that regard, the energy efficiency rating appears as one specific fridge attribute whose relative appeal increases with income particularly strongly. This result carries an important message in terms of the technological features that firms should aim at improving if they wish to increase their penetration into richer markets. Furthermore, the implications of this finding extend beyond the refrigerator industry. Almost all household appliances in the European Union must include an energy efficiency label. Therefore, as long as consumers' valuation of energy efficiency behaves similarly across other household appliances, access to richer markets by firms in these industries may increase dramatically following improvements that lead to more energy-efficient appliances.

The presence of nonhomothetic preferences in the context of costly international transportation (as is the case for bulky goods such as refrigerators) gives prominence to how local demand patterns impact production location choices by firms. We have shown that higher-quality fridge models tend to be manufactured in richer countries. A home-market effect seems to be among the drivers of such production location choices. Furthermore, our results suggest that home-market considerations seem to be powerful enough to drive location decisions in terms of quality specialization across different firms and within firms with multiple plants located in various countries.

One caveat concerning our results on vertical specialization is that our analysis takes the set of manufacturing locations as given. As a consequence, it abstracts from studying dynamic aspects of specialization, such as decisions on opening new plants in additional locations with the purpose of specializing in certain types of quality. Exploring these dynamics can shed new light on how the intensity of the home-market effect responds to major shocks like decline in transportation costs, the negotiation of free trade agreements or preferential change in tariffs or trade barriers, as well as the impact of long phases of economic growth by underdeveloped regions.[56] We leave these dynamic questions open for future research.

[56] There is anecdotal evidence of large brands opening new plants recently in less developed economies so as to take advantage of free trade agreements. For example, Electrolux decided to open a major new refrigerator factory in Thailand (Rayong) in 2015 with the main intention to cater to the type of demand originating from the Asean Economic Community. Similarly, Bosch is planning to open before the end of 2022 their first plant in Mexico (Monterrey), with the intention of targeting the needs in refrigeration appliances of North American consumers. On similar vein, the response to a home-market effect seems to have been a key driver for Liebherr to open their first production site in India (Aurangabad) in 2018, citing as motivation their expectation that demand for higher-quality refrigerators will expand substantially in the years ahead there owing to continual positive economic growth.

References

Alfaro, L., Antràs, P., Chor, D., and Conconi, P. (2019). 'Internalizing Global Value Chains: A Firm-Level Analysis', *Journal of Political Economy*, vol. 127, 509-559.

Andrews, I., Stock, J. H., and Sun, L. (2019). 'Weak instruments in instrumental variables regression: Theory and practice', *Annual Review of Economics*, vol. 11, 727-753.

Antoniades, A., and Zaniboni, N. (2016). 'Exchange rate pass-through into retail prices', *International Economic Review*, 57(4), 1425-1447.

Antràs, P., and Chor, D. (2018). 'On the Measurement of Upstreamness and Downstreamness in Global Value Chains', in *World Trade Evolution: Growth, Productivity and Employment*, ch. 5, 126-194.

Amiti, M. and Khandelwal, A. (2013). 'Import competition and quality upgrading', *Review of Economics and Statistics*, vol. 95, 476-490.

Auer, R., Chaney, T. and Saure, P. (2018). 'Quality pricing-to-market', *Journal of International Economics*, vol. 110, 87-102.

Bastos, P. and Silva, J. (2010). 'The quality of a firm's exports: Where you export to matters', *Journal of International Economics*, vol. 82, 99-111.

Bastos, P., Silva, J., and Verhoogen, E. (2018). 'Export destinations and input prices', *American Economic Review*, 108(2), 353-92.

Berlingieri, G., Breinlich, H. and Dhingra, S. (2018) 'The impact of trade agreements on consumer welfare—Evidence from the EU Common External Trade Policy', *Journal of the European Economic Association*, vol. 16, 1881–1928.

Berry, S. T. (1994). 'Estimating discrete-choice models of product differentiation', *The RAND Journal of Economics*. 25(2), 242-262.

Berry, S., Levinsohn, J., and Pakes, A. (1995). 'Automobile prices in market equilibrium', *Econometrica*, 63(4), 841-890.

Bonadio, B., Fischer, A. M., and Sauré, P. (2020). 'The speed of exchange rate pass-through', *Journal of the European Economic Association*, 18(1), 506-538.

Brambilla, I., Lederman, D., and Porto, G. (2012). 'Exports, export destinations, and skills', *American Economic Review*, 102(7), 3406-38.

Broda, C., and Weinstein, D. E. (2006). 'Globalization and the gains from variety', *The Quarterly Journal of Economics*, 121(2), 541-585.

Campa, J. M., and Goldberg, L. S. (2005). 'Exchange rate pass-through into import prices', *Review of Economics and Statistics*, 87(4), 679-690.

Chatterjee, A., Dix-Carneiro, R., and Vichyanond, J. (2013). 'Multi-product firms and exchange rate fluctuations', *American Economic Journal: Economic Policy*, 5(2), 77-110.

Chen, N. and Juvenal, L. (2016). 'Quality, trade, and exchange rate pass-through', *Journal of International Economics*, vol. 100, 61-80.

Comin, D., Lashkari, D. and Mestieri, M. (2021). 'Structural change with long-run income and price effects', *Econometrica*, 89(1), 311-374.

Coşar, A. K., Grieco, P. L., Li, S., and Tintelnot, F. (2018). 'What drives home market advantage?' *Journal of International Economics*, vol. 110, 135-150.

Crino, R. and Ogliari, L. (2017). 'Financial imperfections, product quality, and international trade', *Journal of International Economics*, vol. 104, 63-84.

Crozet, M., Head, K. and Mayer, T. (2012). 'Quality sorting and trade: Firm-level evidence for French wine', *Review of Economic Studies*, vol. 79, 609-644.

Dingel, J. (2017). 'The determinants of quality specialization', *Review of Economic Studies*, vol. 84, 1551-1582.

Eaton, J., and Kortum, S. (2002). 'Technology, geography, and trade,' *Econometrica* 70(5), 1741-1779.

Fajgelbaum, P., Grossman, G. and Helpman, E. (2011). 'Income distribution, product quality, and international trade', *Journal of Political Economy*, vol. 119, 721-765.

Fajgelbaum, P., Grossman, G. and Helpman, E. (2015). 'A Linder hypothesis for foreign direct investment', *Review of Economic Studies*, vol. 82, 83-121.

Feenstra, R.C. and Romalis, J. (2014). 'International prices and endogenous quality', *Quarterly Journal of Economics*, vol. 129(2), 477-527.

Fieler, A. C., Eslava, M., and Xu, D. Y. (2018). 'Trade, quality upgrading, and input linkages: Theory and evidence from Colombia', *American Economic Review*, 108(1), 109-46.

Finlay, K., and Magnusson, L. M. (2009). 'Implementing weak-instrument robust tests for a general class of instrumental-variables models', *The Stata Journal*, 9(3), 398-421.

Goetz, D., and Rodnyansky, A. (2021). 'Exchange rate shocks and quality adjustment', *Review of Economics and Statistics*, forthcoming.

Goldberg, P., and Hellerstein, R. (2013). 'A structural approach to identifying the sources of local currency price stability', *Review of Economic Studies*, 80(1), 175-210.

Goldberg, P. K., and Verboven, F. (2001). 'The evolution of price dispersion in the European car market', *The Review of Economic Studies*, 68(4), 811-848.

Hallak, J. C. (2006). 'Product quality and the direction of trade', *Journal of Interna-*

tional Economics, vol. 68, 238-265.

HANDBURY, J. (2021). 'Are Poor Cities Cheap for Everyone? Non-Homotheticity and the Cost of Living Across U.S. Cities', *Econometrica*, 89(6), 2679-2715.

HANOCH, G. (1975). 'Production and Demand Models with Direct or Indirect Implicit Additivity', *Econometrica*, 43(2), 395-419.

HEINS, G. (2020). 'Endogenous vertical differentiation, variety, and the unequal gains from trade', mimeo.

HUMMELS, D., AND SKIBA, A. (2004). 'Shipping the good apples out? An empirical confirmation of the Alchian-Allen conjecture', *Journal of Political Economy*, 112(6), 1384-1402.

HUMMELS, D. AND KLENOW, P. (2005). 'The variety and quality of a nation's exports', *American Economic Review*, vol. 95, 704-723.

JAIMOVICH, E. AND MERELLA, V. (2012). 'Quality ladders in a Ricardian model of trade with nonhomothetic preferences', *Journal of the European Economic Association*, vol. 10, 908-937.

JAIMOVICH, E. AND MERELLA, V. (2015). 'Love for quality, comparative advantage, and trade', *Journal of International Economics*, vol. 97, 376-391.

KHANDELWAL, A. (2010). 'The long and short (of) quality ladders', *Review of Economic Studies*, vol. 77, 1450-1476.

KHANDELWAL, A., SCHOTT, P. AND WEI S. (2013). 'Trade liberalization and embedded institutional reform: Evidence from Chinese exporters', *American Economic Review*, vol. 103, 2169-2195.

LASHKARIPOUR, A. (2020). 'Weight-based quality specialization,' *Journal of International Economics*, vol. 127.

LINDER, S. (1961). *An essay on trade and transformation*, Uppsala: Almqvist & Wiksell.

MANOVA, K. AND ZHANG, Z. (2012). 'Export prices across firms and destinations', *Quarterly Journal of Economics*, vol. 127, 379-436.

MANOVA, K. (2013). 'Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector', *Review of Economic Studies*, vol. 80, 711-744.

MATSUYAMA, K. (2019). 'Engel's law in the global economy: Demand?induced patterns of structural change, innovation, and trade', *Econometrica*, 87(2), 497-528.

MEJEAN, I. AND MARTIN, J. (2014). 'Low-wage countries' competition, reallocation across firms and the quality content of exports', *Journal of International Economics*, vol. 93, 140-152.

OLEA, J. L. M., AND PFLUEGER, C. (2013). 'A robust test for weak instruments', *Journal of Business & Economic Statistics*, 31(3), 358-369.

Nakamura, E., and Zerom, D. (2010). 'Accounting for incomplete pass-through', *The Review of Economic Studies*, 77(3), 1192-1230.

Petrin, A. (2002). 'Quantifying the benefits of new products: The case of the minivan', *Journal of Political Economy*, 110(4), 705-729.

Piveteau, P. and Smagghue, G. (2019). 'Estimating firm product quality with trade data', *Journal of International Economics*, vol. 118, 217-232.

Piveteau, P. and Smagghue, G. (2020). 'Foreign competition along the quality ladder', mimeo.

Rios-Avila, F. (2015). Feasible fitting of linear models with N fixed effects. *The Stata Journal*, 15(3), 881-898.

Schott, P. (2004). 'Across-product versus within-product specialization in international trade', *Quarterly Journal of Economics*, vol. 119, 647-678.

Sheu, G. (2014). 'Price, Quality, and Variety: Measuring the Gains from Trade in Differentiated Products", *American Economic Journal: Applied Economics*, vol. 6, 66-89.

Simonovska, I. (2015). 'Income differences and prices of tradables: Insights from an online retailer', *Review of Economic Studies*, vol. 82, 1612-56.

Sit, D. (2015). 'Manufacturing of Refrigerators', in *Services in Global Value Chains: Manufacturing-Related Services*, ch. 12, 247-264.

Verhoogen, E. (2008). 'Trade, quality upgrading and wage inequality in the Mexican manufacturing sector', *Quarterly Journal of Economics*, vol. 123, 489-530.

Appendix

A.1 Additional Theoretical and Empirical Results

A.1.1 Additional Theoretical Results

A.1.1.1 Representative Household's Problem – Homothetic Case

The country-i representative agent's problem consists of maximising the value of the objective function (1) subject to the budget constraint

$$\sum_{s\in\mathcal{S}}\sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t}q_{i,j_s,t} \leq P_{i,t}Y_{i,t} \tag{A.29}$$

where $P_{i,t}$ is the price index associated to $Y_{i,t}$.

In order to solve the representative agent's problem, we may write the Lagrangian

$$\mathcal{L} = \prod_{s\in\mathcal{S}}\left(\sum_{j_s\in\mathcal{J}_{s,t}} \lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}\right)^{\frac{\alpha_s\sigma_s}{\sigma_s-1}} + \nu\left(P_{i,t}Y_{i,t} - \sum_{s\in\mathcal{S}}\sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t}q_{i,j_s,t}\right)$$

from which we obtain the first-order conditions

$$\frac{\partial\mathcal{L}}{\partial q_{i,j_s,t}} = \frac{\alpha_s}{q_{i,j_s,t}}\frac{\lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}}{\sum_{j_s\in\mathcal{J}_{s,t}}\lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}}C_{i,t} - \nu p_{i,j_s,t} = 0, \quad \forall t,\ j_s\in\mathcal{J}_{s,t},\ s\in\mathcal{S},\ i\in\mathcal{I} \tag{A.30}$$

Rearranging, multiplying the whole expression by $q_{i,j_s,t}$ and summing over the set $\mathcal{J}_{s,t}$ yields

$$\alpha_s\frac{\sum_{j_s\in\mathcal{J}_{s,t}}\lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}}{\sum_{j_s\in\mathcal{J}_{s,t}}\lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}}C_{i,t} = \alpha_s C_{i,t} = \nu\sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t}q_{i,j_s,t}$$

Furthermore, summing over the set $\mathcal{S}$ and imposing the parameter restriction $\sum_{s\in\mathcal{S}}\alpha_s = 1$, we have

$$C_{i,t} = \sum_{s\in\mathcal{S}}\alpha_s C_{i,t} = \nu\sum_{s\in\mathcal{S}}\sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t}q_{i,j_s,t} = \nu P_{i,t}C_{i,t}$$

from which we learn that the Lagrange multiplier equals the reciprocal of the price index, i.e. $\nu = P_{i,t}^{-1}$.

Replacing this result into (A.30) and rearranging, we obtain the country-i demand function of variety j_s in period t

$$q_{i,j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} C_{i,t}^{\sigma_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{-\sigma_s} p_{i,j_s,t}^{-\sigma_s} \lambda_{i,j_s} \tag{A.31}$$

Using the definition of $Q_{i,s,t}$, we have

$$Q_{i,s,t} \equiv \sum_{j_s \in \mathcal{J}_{s,t}} q_{j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} C_{i,t}^{\sigma_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{-\sigma_s} \sum_{j_s \in \mathcal{J}_{s,t}} p_{j_s,t}^{-\sigma_s} \lambda_{i,j_s} \tag{A.32}$$

imposing the identity $m_{i,j_s,t} \equiv q_{i,j_s,t}/Q_{i,s,t}$, using (A.31), (A.32), (2) and simplifying, we obtain (3).

A.1.1.2 Representative Household's Problem – Nonhomothetic case

Preliminarily, recall the utility function

$$\prod_{s \in \mathcal{S}} \left[\left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s} = 1, \tag{A.33}$$

and notice that, if we let $\varepsilon_{j_s} = 1$ for all j_s, imposing the parameter restriction $\sum_{s=1}^{S} \alpha_s = 1$, we can obtain again the classical homothetic version of CES aggregator used in Section 3. Namely,

$$\begin{aligned}
1 &= \prod_{s \in \mathcal{S}} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{1-\sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\alpha_s \sigma_s}{\sigma_s - 1}} = \prod_{s \in \mathcal{S}} Y_{i,t}^{-\alpha_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\alpha_s \sigma_s}{\sigma_s - 1}} \\
&= Y_{i,t}^{-\sum_{s \in \mathcal{S}} \alpha_s} \prod_{s \in \mathcal{S}} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\alpha_s \sigma_s}{\sigma_s - 1}} = Y_{i,t}^{-1} \prod_{s \in \mathcal{S}} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\alpha_s \sigma_s}{\sigma_s - 1}}, \\
Y_{i,t} &= \prod_{s \in \mathcal{S}} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\alpha_s \sigma_s}{\sigma_s - 1}}.
\end{aligned}$$

Turn now to consider country-i representative agent's expenditure minimization problem, with the expenditure defined by

$$\sum_{s \in \mathcal{S}} \sum_{j_s \in \mathcal{J}_{s,t}} p_{i,j_s,t} q_{i,j_s,t} \equiv P_{i,t} Y_{i,t}, \tag{A.34}$$

where $P_{i,t}$ is the price index associated to $Y_{i,t}$, and constrained by the preference representation as in (A.33). Letting ν denote the Lagrange multiplier on the constraint (A.33), we may write the Lagrangian

$$\mathcal{L} = \sum_{s\in\mathcal{S}} \sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t} q_{i,j_s,t} + \nu \left[1 - \prod_{s\in\mathcal{S}} \left(\sum_{j_s\in\mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s}-\sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}} \right)^{\frac{\alpha_s\sigma_s}{\sigma_s-1}} \right],$$

from which we obtain the first-order condition

$$\frac{\partial \mathcal{L}}{\partial q_{i,j_s,t}} = p_{i,j_s,t} - \nu \frac{\alpha_s}{q_{i,j_s,t}} \frac{\lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s}-\sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}}{\sum_{j_s\in\mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s}-\sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}} = 0, \tag{A.35}$$

where we have assumed that the budget constraint binds.

Rearranging, multiplying both sides by $q_{i,j_s,t}$ and summing over varieties yields

$$\sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t} q_{i,j_s,t} = \nu\alpha_s.$$

Furthermore, summing over goods, using the definition of expenditure and the parameter restriction $\sum_{s=1}^{S} \alpha_s = 1$, we get

$$P_{i,t} Y_{i,t} = \sum_{s\in\mathcal{S}} \sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t} q_{i,j_s,t} = \nu \sum_{s\in\mathcal{S}} \alpha_s = \nu.$$

Replacing this result into (A.35) and rearranging, we obtain the country-i demand function of variety j_s in period t

$$q_{i,j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} \left(\sum_{j_s\in\mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s}-\sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}} \right)^{-\sigma_s} p_{i,j_s,t}^{-\sigma_s} Y_{i,t}^{\varepsilon_{j_s}} \lambda_{i,j_s,t}. \tag{A.36}$$

Using the definition of $Q_{i,s,t}$, we have

$$Q_{i,s,t} \equiv \sum_{j_s\in\mathcal{J}_{s,t}} q_{j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} \left(\sum_{j_s\in\mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s}-\sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}} \right)^{-\sigma_s} \sum_{j_s\in\mathcal{J}_{s,t}} p_{i,j_s,t}^{-\sigma_s} Y_{i,t}^{\varepsilon_{j_s}} \lambda_{i,j_s,t}. \tag{A.37}$$

Imposing the identity $m_{i,j_s,t} \equiv q_{i,j_s,t}/Q_{i,s,t}$, using (A.36), (A.37) and (2), simplifying and dropping the subscript s, we obtain (10).

A.1.1.3 Firm's Problem – Production Location

The firm maximizes profit by choosing the price to optimally charge in country i when model j is produced in country k, taking the demand function (17) into account and facing the marginal cost $c_{k,j}$ and the transportation cost $\tau_{k,i}$; formally:

$$\Pi_{i,j}^{k} = \max_{p_{i,j}^{k}} \left(p_{i,j}^{k} - \tau_{k,i} c_{k,j}\right) \Omega_i \lambda_j \left(p_{i,j}^{k}\right)^{-\sigma} Y_i^{\tilde{\kappa}(\lambda_j)}, \tag{A.38}$$

which leads to the first order condition:

$$\frac{\partial \Pi_{i,j}^{k}}{\partial p_{i,j}^{k}} = 1 - \sigma \left(p_{i,j}^{k} - \tau_{k,i} c_{k,j}\right) \left(p_{i,j}^{k}\right)^{-1} = 0. \tag{A.39}$$

We obtain (18) by simply isolating $p_{i,j}^{k}$ in (A.39). We may plug (18) into (A.38), which yields:

$$\Pi_{i,j}^{k} = \left(\tau_{k,i} c_{k,j} \frac{1}{\sigma - 1}\right) \Omega_i \lambda_j \left(\tau_{k,i} c_{k,j} \frac{\sigma}{\sigma - 1}\right)^{-\sigma} Y_i^{\tilde{\kappa}(\lambda_j)},$$

and, rearranging, leads to (19). The total profit (20) earned by the firm when model j is produced in country k results from the sum of (19), computed first with reference to $i = h$ and then to $i = l$. The profit ratio (21) is straightforwardly obtained by dividing (20) computed with reference to $k = h$ by the same expression computed with reference to $k = l$, and rearranging.

Proof of Lemma 1. Differentiating (21) with respect to λ_i yields:

$$\frac{\partial \varpi_j}{\partial \lambda_i} = \left(\frac{c_{l,j}}{c_{h,j}}\right)^{\sigma-1} \Upsilon'\left(\lambda_j\right) > 0,$$

where the inequality follows from noticing that $\Upsilon'\left(\lambda_j\right) > 0$. $\square$

Plugging the definition of marginal cost $c_{k,j} = \omega_k / \zeta_{k,j}$ into (21), we have:

$$\varpi_j = \left(\frac{\omega_l \zeta_{h,j}}{\omega_h \zeta_{l,j}}\right)^{\sigma-1} \Upsilon\left(\lambda_j\right),$$

which imposing the inequality $\varpi_j > 1$, after raising the whole expression to the power $1/\left(\sigma - 1\right)$ and rearranging, leads to (23).

Condition (23) implies that the probability that model j is produced in country h is

$$\Pr_j^h = \Pr\left(\Pi_j^h > \Pi_j^l\right) = 1 - \Pr\left(\zeta_{h,j} \le \zeta_{l,j}\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega\right).$$

Under the assumption that $\zeta_{k,j}$ follows a Frechet distribution, the probability density function reads

$$f_{k,j}\left(\zeta\right) = \delta T_{k,j}^{\delta}\zeta^{-1-\delta}\exp\left(-T_{k,j}^{\delta}\zeta^{-\delta}\right).$$

Together with (22), the last two expressions imply

$$\begin{aligned}\Pr_j^h &= 1 - \int_0^\infty \exp\left(-T_{h,j}^{\delta}\left[\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega\right]^{-\delta}\zeta_{l,j}^{-\delta}\right)\delta T_{l,j}^{\delta}\zeta_{l,j}^{-1-\delta}\exp\left(-T_{l,j}^{\delta}\zeta_{l,j}^{-\delta}\right)d\zeta_{l,j},\\ &= 1 - \int_0^\infty \delta T_{l,j}^{\delta}\zeta_{l,j}^{-1-\delta}\exp\left(-\left\{T_{h,j}^{\delta}\left[\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega\right]^{-\delta} + T_{l,j}^{\delta}\right\}\zeta_{l,j}^{-\delta}\right)d\zeta_{l,j}\end{aligned}$$

which after some algebra leads to

$$\Pr_j^h = 1 - \frac{T_{l,j}^{\delta}}{\Lambda}\int_0^\infty \delta\Lambda\zeta_{l,j}^{-1-\delta}\exp\left(\left\{-\Lambda\zeta_{l,j}^{-\delta}\right\}\right)d\zeta_{l,j} = 1 - \frac{T_{l,j}^{\delta}}{\Lambda},$$

where $\Lambda \equiv T_{h,j}^{\delta}\left[\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega\right]^{-\delta} + T_{l,j}^{\delta}$, and thereby to (24).

Proof of Proposition 1. Denote $\Psi\left(\lambda_j\right) \equiv \left(1+\lambda_j\right)^{\psi(1/A_h-1/A_l)} \ge 1$, and note that $\Psi\left(\lambda_j\right)$ has partial derivative with respect to λ_j

$$\Psi'\left(\lambda_j\right) = -\psi\frac{A_h - A_l}{A_l A_h}\Psi\left(\lambda_j\right)\ln\left(1+\lambda_j\right) \le 0.$$

Differentiating (24) with respect to λ_j, we obtain

$$\frac{\partial \Pr_j^h}{\partial \lambda_j} = \Upsilon'\left(\lambda_j\right)\frac{\partial \Pr_j^h}{\partial \Upsilon\left(\lambda_j\right)} + \Psi'\left(\lambda_j\right)\frac{\partial \Pr_j^h}{\partial \Psi\left(\lambda_j\right)}.$$

Furthermore,

$$\frac{\partial \Pr_j^h}{\partial \Upsilon\left(\lambda_j\right)} = \frac{\delta}{\sigma-1}\frac{A_l}{A_h}\Psi\left(\lambda_j\right)\Upsilon\left(\lambda_j\right)^{-\frac{\delta}{\sigma-1}-1}\omega^{\delta}\left(\Pr_j^h\right)^2 > 0,$$

and

$$\frac{\partial \Pr_j^h}{\partial \Psi\left(\lambda_j\right)} = -\frac{A_l}{A_h}\left[\Upsilon\left(\lambda_j\right)^{-\frac{1}{\sigma-1}}\omega\right]^{\delta}\left(\Pr_j^h\right)^2 < 0.$$

The statement in Case 1 straightforwardly follows from noticing that $\psi = 0$ implies $\Psi'\left(\lambda_j\right) = 0$; otherwise, $\Psi'\left(\lambda_j\right) > 0$, which leads to Case 2. □

Procedure to estimate $b \equiv \xi \cdot \psi$. In the model in Section 5, the marginal cost of producing variety j in country k is given by $c_{k,j} = w_k/\zeta_{k,j}$. In addition, given the CES structure of preferences and monopolistic competition, prices are proportional to the marginal cost: $p_{k,j} = \chi c_{k,j}$, with $\chi > 1$. As a result, we can write

$$\ln \zeta_{k,j} = \ln w_k - \ln p_{k,j} - \widetilde{\chi}, \tag{A.40}$$

where $\widetilde{\chi} \equiv \ln(\chi) > 0$ reflects the mark-up. Next, notice that since ζ follows a Fréchet distribution with location parameter $T_{k,j}$ and shape parameter equal to δ, $\ln \zeta$ follows a Gumbel distribution with cumulative distribution function

$$F_{k,j}(\ln \zeta) = \exp\left(-e^{-\delta\left(\ln \zeta - \ln T_{k,j}\right)}\right).$$

Using thus the properties of the Gumbel distribution,

$$E_{k,j}(\ln \zeta) = \ln T_{k,j} + \gamma/\delta, \tag{A.41}$$

where γ is the so-called Euler–Mascheroni constant (so, $\gamma \simeq 0.577$).

By using (A.40) and (A.41), we can obtain the following expression for the expected value of the market price of variety j:

$$E(\ln p_{k,j}) = \ln w_k - \ln T_{k,j} + \widetilde{\gamma},$$

where $\widetilde{\gamma} \equiv \widetilde{\chi} + \gamma/\delta$. Using now the fact that $T_{k,j} \equiv A_k^{\alpha}(1 + \xi\lambda_j)^{-(1+\psi/A_k)}$ and approximating $\ln(1 + \xi\lambda_j) \simeq \xi\lambda_j$, we can finally obtain

$$E(\ln p_{k,j}) = \varpi_k + \xi\lambda_j + \xi\psi\frac{\lambda_j}{A_k} + \widetilde{\gamma}, \tag{A.42}$$

where $\varpi_k \equiv \ln w_k - \ln(A_k)$.

To carry out our regression analysis we will take into account the time variation present in our data (t) and also the fact that variety j is sold in several destination markets (i). Furthermore, we will take into account that each variety is, in equilibrium, produced in a single location – this entails that we can simply index varieties as $j(k)$, where k is the country where j is manufactured. Based on this considerations, the expression in (A.42) can be operationalized by the following regression equation:

$$\ln p_{i,j(k),t} = a \cdot \lambda_{j(k)} + b \cdot \left(\frac{\lambda_{j(k)}}{A_{k,t}}\right) + \varpi_{k,t} + \varepsilon_{i,j(k),t}. \tag{A.43}$$

The regression equation in (A.43) is missing some important factors that will possibly impact on market prices across destinations and time. One important factor to take into account is the presence of transportation costs between origin and destination countries. In addition, there can also be differences in taxation across destination markets and time that will affect market prices. We will account for these factors by including a set of origin-destination-time fixed effects $\Phi_{i,k,t}$ (note that $\Phi_{i,k,t}$ will render $\varpi_{k,t}$ superfluous, so we can exclude that term from our final regression specification).[57] Another important factor would be country of destination specific preferences for certain varieties (especially in a context with nonhomothetic preferences). We will account for this factor by including destination-model fixed effects $\Delta_{i,j(k)}$. Notice that once we include $\Delta_{i,j(k)}$, these set of dummies will absorb the impact of $\lambda_{j(k)}$ on $\ln p_{i,j(k),t}$.

Our regression equation to identify the impact of the ratio $\lambda_{j(k)}/A_{k,t}$ on $\ln p_{i,j(k),t}$ is thus given by (27). We estimate (27) via OLS, clustering the standard errors by fridge models. Our estimation thus identifies the product $\xi \cdot \psi$. Note that (27) controls for a large set of possible confounders. For example, any source of impact on prices stemming from a country of origin productivity shock (either temporary or permanent) will be captured by $\Phi_{i,k,t}$. In addition, any variation in prices in the destination country i resulting from changes in the competitive environment therein will also be absorbed by $\Phi_{i,k,t}$.[58]

[57]Including the set of fixed effects $\Phi_{i,k,t}$ is feasible since we can exploit the fact that several different models are produced in country k.

[58]Possible bias to our estimation of b through OLS would then require the presence of country of origin specific shocks that are quality-specific as well. That could lead to a downwards bias in our OLS estimate of b through its correlation with $\lambda_{j(k)}$. On the other hand, it could as well be that positive shocks to the productivity of high-quality models are more common to take place in countries with high values of the endowment $A_{k,t}$, which would instead cause of OLS estimate of b to be upwards bias. Unfortunately, we do not have good instruments in our dataset for the ratio $\lambda_{j(k)}/A_{k,t}$ that could identify b more credibly than our OLS estimates.

Table A.1 – Description of Product Characteristics

Characteristics	Description
	Vertical
Annual energy use	Annual energy consumption measured in kilowatt hours per year based on the formula: $AE = E_{24h} * 365$, where E_{24h} is the energy use of a refrigerating appliance in kWh/24h.
Display	Any screen or other visual technology for displaying information (e.g. compartment temperature) and/or as a digital control panel.
Energy label	The EU energy label for refrigerating appliances is an attributes-based label, which is assigned based on the calculation of an Energy Efficiency Index. The index depends not only on annual kWh consumption of a fridge, but also on the number of compartments and their storage volume and nominal temperature, presence of frost-free system, type of construction, and various other characteristics. The EU Energy Label Directive defines labels from A+++ (most efficient) to G (least efficient), but currently Minimum Performance Standards via the Ecodesign Directive only allow refrigerators with labels A+ and above to be sold on the European Common Market.
Freezer on side	A dummy variable equal to one if a freezer is positioned in the right or left part of at least two-doors refrigerating appliance, and zero if a freezer position is on top/bottom.
Metal Exterior	A dummy variable equal to one if the exterior finish (material and colour) of a refrigerating appliance's door is aluminium, silver, stainless steel, glass/mirror, or has a metal look.
No-frost system	An indicator variable for the presence of a no-frost system. Such a system consists of integrated centrifugal fans, which circulate air to keep the evaporator free from condensate and ice, thus eliminating the need for manual defrosting.
Noise level	Noise level of a refrigerating appliance measured in decibel, usually caused by condenser and evaporator fans as well as compressors.
Water/ice dispenser	A dummy variable equal to one if a refrigerating appliance has a water dispenser and/or ice-cube dispenser.
Zero-degree box	A dummy variable equal to one if a refrigerating appliance is equipped with a zero-degree zone. This is a pull-out drawer for the storage of fresh produce such as vegetables, fruit and meat, which maintains humidity levels and constant temperature around 0 degrees Celsius through cool-air vents.
	Size
Height/Width (cm)	Overall dimensions (height and width) measured in centimeters. Width is a categorical variable.
Net liters	Total volume in liters of the space within the inside liner of a refrigerating appliance.
Number of doors	Number of doors of a refrigerating appliance.
	Horizontal
Installation	A dummy variable equal to one if a refrigerator is built-in or built-under (i.e. intended to be installed in a cabinet or encased), and zero if it is freestanding.

Notes: The data contains additionally the following variables: *Inverter compressor* – a dummy variable equal to one if a refrigerating appliance's compressor is an inverter type. Compressors move refrigerant through inner and outer heat exchange coils. Unlike conventional single-speed compressors, which either operate at full speed, or are switched off, inverter compressors are always on, but operate at variable speeds. Inverter compressors are more durable, more energy efficient, and generate less noise. We do not make use of this variable as it is missing for 57% of the sample; *mounting system* – an installation system for built-in appliances (fixed door or slide mounting). This variable is perfectly collinear with installation type as only built-in refrigerators have a mounting system. Preferences with regard to type of installation may vary with personal tastes and circumstances. As these characteristics are not directly associated with quality, we classify them as horizontal; *freezer stars* – this characteristic determines the lowest freezing temperature that could be maintained in a freezer. The variable has minimal variation since 99% of all refrigerators in the sample are with a four-star compartment. For further information on refrigerating appliances with regard to energy labels and characteristics' definitions refer to European Commission (2010a), (2010b), (2019)).

A.1.2 Additional Empirical Results

TABLE A.2 – TESTING FOR HETEROGENEOUS PASS-THROUGH

	(1)	(2)
L^{-3} $\ln(ER)$	-0.040	-0.047
	(0.014)***	(0.016)***
L^{-3} $\ln(ER)\times$ High Income	-0.032	
	(0.019)	
L^{-3} $\ln(ER)\times$ High Efficiency		0.020
		(0.043)
Destination-date	Yes	Yes
Product-destin.	Yes	Yes
Brand-year	Yes	Yes
Products	2,217	2,217
N	284,025	284,025

Notes: The table shows results from a modified first-stage estimation of eq (5) testing for heterogeneous pass-through with respect to quality. The dependent variable is ln(Price. In Column (1), the third lag of the log of the exchange rate, L^{-3} $\ln(ER)$ is interacted with a dummy (High Income), which is set to one for products manufactured in Austria, Germany, Denmark, France, Italy, Spain, Sweden, or South Korea. In Column (2), the interaction is with an indicator (High Efficiency) for highly energy efficient products with energy labels A+++, or A++. Standard errors in parentheses are robust and clustered by country. Refer to footnote 22 in the main text for further discussion. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3 – Measures of Quality: Comparison

	log(Price)	$\widehat{\theta}_j^h$	$\widehat{\theta}_j^{nh}$
	(1)	(2)	(3)
A+++	0.145	0.599	2.626
	(0.063)**	(0.139)***	(0.244)***
A++	0.017	0.312	2.193
	(0.066)	(0.118)**	(0.184)***
A+	-0.045	0.153	1.383
	(0.046)	(0.103)	(0.157)***
A	-0.048	0.067	0.419
	(0.040)	(0.091)	(0.121)***
Zero-degree box	0.214	0.342	0.149
	(0.094)**	(0.144)**	(0.046)***
Freezer side	0.549	0.812	0.248
	(0.052)***	(0.061)***	(0.075)***
Dispenser	0.120	0.246	0.080
	(0.063)*	(0.078)***	(0.056)
No-frost system	0.224	0.277	0.465
	(0.049)***	(0.098)***	(0.059)***
ln(Noise Level)	-0.454	-1.449	-1.656
	(0.338)	(0.612)**	(0.640)**
Display	0.202	0.221	-0.031
	(0.026)***	(0.026)***	(0.059)
Metal exterior	0.054	0.101	0.061
	(0.015)***	(0.038)**	(0.045)
№ doors	0.198	0.396	0.198
	(0.041)***	(0.048)***	(0.067)***
Brand	Yes	Yes	Yes
N	2,069	2,069	2,069
R^2	0.774	0.663	0.635

Notes: This table repeats Columns (2) and (6) from Table 5 and compares these results to a measure of quality derived under the assumption of nonhomothetic preferences. The dependent variable is the log of Price in Column (1), inferred quality based on eq (6) under homothetic-preferences assumption in Column (2), and inferred quality based on eq (16) under a nonhomothetic-preferences assumption in Column (3). Both quality measures are standardized to allow for comparability of coefficient estimates. Physical characteristics are explained in Table A.1, while Table 2 provides descriptive statistics. All standard errors are robust and clustered by brand. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4 – Price Elasticity: Controlling for Market Age

	(1)	(2)	(3)	(4)
Preferences assumption	Homothetic		Nonhomothetic	
		ER $\neq$1		
log(Price)	-4.247	-5.480	-5.121	-4.065
	(2.333)*	(2.905)*	(2.603)*	[3.154]
$\widehat{\theta}_j^{nh} \times \ln(Y)$				4.539
				[1.969]**
$mage_{y,i}$	Yes	Yes	Yes	Yes
N	284,022	185,123	272,734	272,734

Notes: The table replicates columns (5) and (6) of Table 3 and columns (2) and (3) of Table 6, but in addition controls for the number of years a model is sold in a given country relative to the first year of its entry into the specific country's market y interacted with country fixed effects ($mage_{y,i}$). As in Table 6, standard errors in brackets are bootstrapped based on 500 replications and resampling by country, where the bootstrapping procedure accounts for all stages of the estimation. Refer to the notes under Tables 3 and 6 for further details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5 – Testing for Non-homothetic Preferences: Subsample of Models with Similar Degree of Market Competition

	(1)	(2)	(3)
Quality measure:	Homothetic	Non-homothetic	
		1st Step	2nd Step
log(Price)	-5.705	-6.022	-4.556
	(2.746)**	(2.874)**	(2.947)
$\widehat{\theta}_j \times \ln(Y)$	1.515		
	(0.392)***		
$\widehat{\theta}_j^{nh} \times \ln(Y)$			3.941
			(1.035)***
Product-destination	Yes	Yes	Yes
Destination-date	Yes	Yes	Yes
Brand-year	Yes	Yes	Yes
Attributes $\times \ln(Y)$	No	Yes	No
N	248,025	236,807	236,807

Notes: This table reports the results of the same regressions as those performed in Table 6, but discarding from the sample all the models that are sold in markets that belong to the bottom quartile in terms of coefficient of variation of the distribution of 'energy efficiency' (measured on a scale from 0 to 4). The rationale for discarding these models is to restrict the sample to follow only models facing a sufficiently similar competition conditions by alternative models in the market. Robust standard errors clustered at the country level are reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6 – Quality and Production Location: Additional variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:					$\widehat{\theta}_j^{nh}$					
log(GDP p.c.)	0.600	0.639	0.604	0.615	0.546	0.431	1.050	0.438	0.507	0.403
	0.191)***	(0.274)**	(0.179)***	(0.199)***	(0.224)**	(0.134)***	(0.420)**	(0.119)***	(0.125)***	(0.158)**
Physical Capital Stock p.c.	-0.019					-0.026				
	(0.065)					(0.056)				
Rule of Law Index		-0.026					-0.440			
		(0.130)					(0.187)**			
log(Population)			0.045					0.073		
			(0.065)					(0.057)		
log(Area)				0.016					0.081**	
				(0.057)					(0.031)	
log(Distance)					-0.242					-0.248
					(0.529)					(0.644)
Brand FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
N	2,069	2,069	2,069	2,069	2,069	2,068	2,068	2,068	2,068	2,068
R^2	0.072	0.072	0.076	0.072	0.075	0.282	0.313	0.286	0.291	0.282

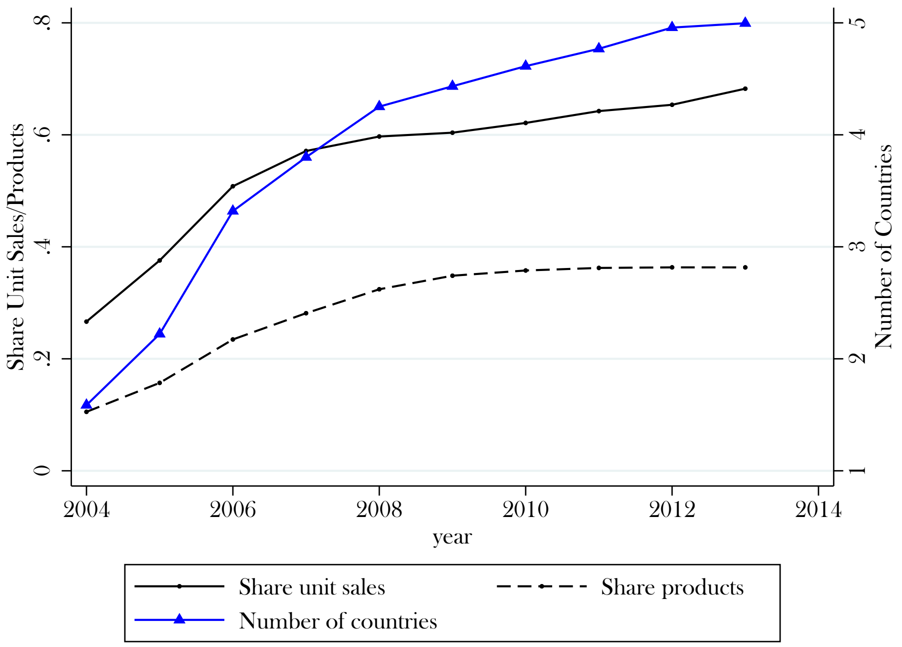
Notes: The table shows results from an OLS estimation in which the dependent variable is the inferred quality measure defined by eq. (14). The regressors, which refer to the country where models are produced, are time averages over the observed life cycle of each model, which is measured from the first to the last year the model is supplied to any destination country in the data. GDP, physical capital stock, and population (to compute per-capita values) are retrieved from the Penn World Tables. Rule of law and area are taken from the World Bank database. Bilateral distances are retrieved from the CEPII dataset, using intra-country agglomeration weighted measures. Robust standard errors clustered at the level of brand and country of origin in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A.7 – ESTIMATION OF $b \equiv \xi \cdot \psi$

Dependent variable:		$\ln p_{i,j(k),t}$	
	(1)	(2)	(3)
$\lambda_{j(k)}$/Human Capital Index	0.965		
	(0.578)*		
$\lambda_{j(k)}$/LOG(Fin. Dev. Index)		0.001	
		(0.001)	
$\lambda_{j(k)}$/Physical Capital Stock p.c.			-0.228
			(0.233)
Destination-Origin-Period FE	Yes	Yes	Yes
Model-Destination FE	Yes	Yes	Yes
N	240,800	242,529	242,954

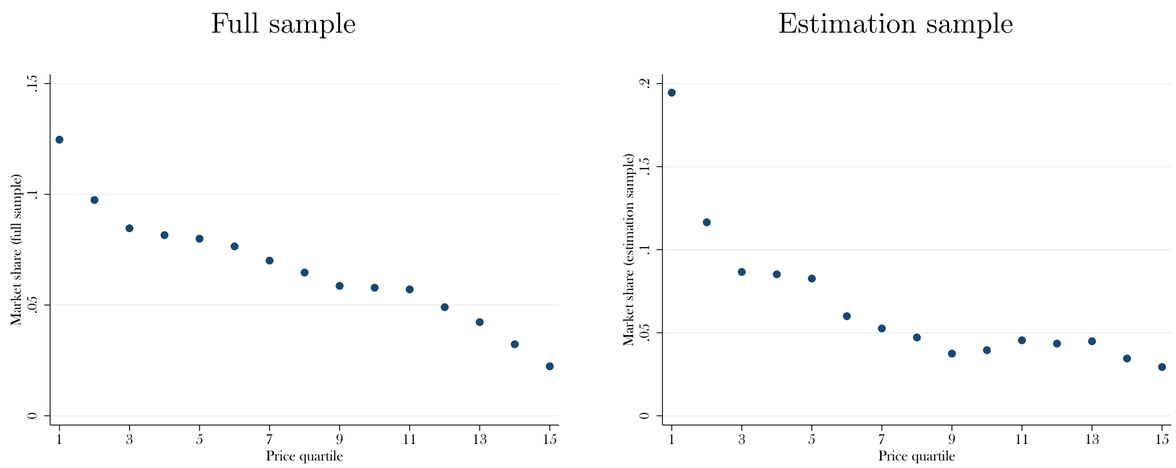
Notes: Robust standard errors are clustered at the model level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1 – Refrigerators: Trends in Multi-Country Trade



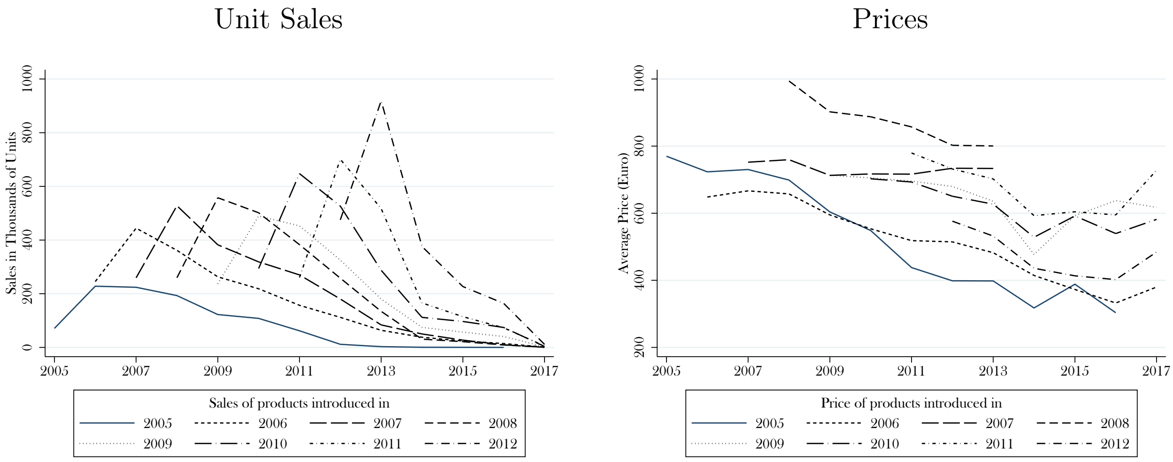
Notes: The solid line depicts the share of units sales of refrigerators traded in more than one country from all units sold in a year. The dashed line is the number of refrigerators sold in more than one country relative to the total number of products in a given year. The plot is based on the raw EU data.

Figure A.2 – Market Share across Price Quantiles in Full and Estimation Samples



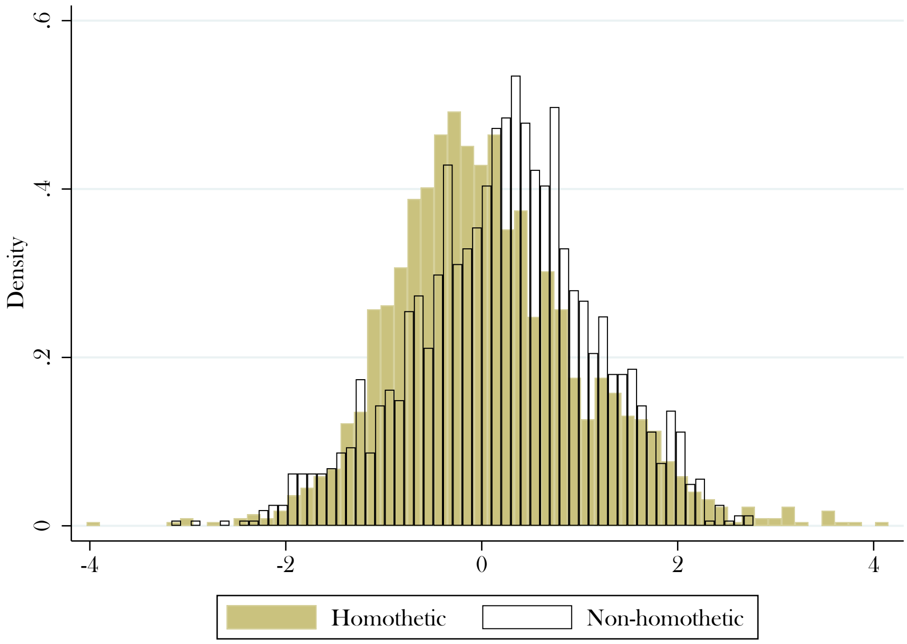
Notes: The figure depicts market shares (total units sold per quantile over total units sold in the panel) over fifteen price quantiles for the full sample (left) as summarized in Panel B of Table 1 and the estimation sample (right) summarized in Panel C of Table 1. The price range of the quantile categories is held constant across the two samples.

Figure A.3 – Unit Sales and Prices over the Life-cycle



Notes: The figure depicts the yearly evolution in total unit sales (left) and average prices (right) by cohorts of models first entering the market in 2005, 2006, up to 2012 based on the estimation sample summarized in Panel C of Table 1. Note that the figure also reflects compositional effects as a given cohort may be sold in a different (mostly declining) set of countries over time.

Figure A.4 – Inferred Quality Estimates Distribution



Notes: The figure plots the distribution of the quality index for 2,217 products. The quality index is the residual estimate from specification 3 in Table 3 and is obtained based on the formula in eq. (6). The data is then collapsed at the product level.

References

EUROPEAN COMMISSION, 2010. Directive 2010/30/EU of the European Parliament and of the Council of 19 May 2010 on the indication by labelling and standard product information of the consumption of energy and other resources by energy-related products. *Official Journal of the European Union* L 153/1.

EUROPEAN COMMISSION, 2010. Commission delegated regulation (EU) No 1060/2010 of 28 September 2010 supplementing Directive 2010/30/EU of the European Parliament and of the Council with regard to energy labelling of household refrigerating appliances. *Official Journal of the European Union* L 314/17.

EUROPEAN COMMISSION , 2019. Commission delegated regulation (EU) 2019/2016 of 11 March 2019 supplementing Regulation (EU) 2017/1369 of the European Parliament and of the Council with regard to energy labelling of refrigerating appliances and repealing Commission Delegated Regulation (EU) No 1060/2010. *Official Journal of the European Union* L 315/102.