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**INSIDE THE WHITE BOX: UNPACKING THE DETERMINANTS
OF QUALITY AND VERTICAL SPECIALIZATION**

By

Esteban Jaimovich
(University of Surrey),

Boryana Madzharova
(University of Erlangen-Nuremberg),

&

Vincenzo Merella
(Università degli Studi di Cagliari).

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School of Economics
University of Surrey
Guildford
Surrey GU2 7XH, UK
Telephone +44 (0)1483 689380
Facsimile +44 (0)1483 689548

Web <https://www.surrey.ac.uk/school-economics>

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

Esteban Jaimovich, Boryana Madzharova, Vincenzo Merella[†]

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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 literature, model-level data allow us to test for the presence of nonhomotheticities 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 levels of income, 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 such patterns of quality specialization are driven mainly by a home-market effect linked to nonhomothetic preferences.

JEL Classification: F1; F14

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

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[†]Jaimovich: University of Surrey, Guildford, Surrey, GU2 7XH, UK, e.jaimovich@surrey.ac.uk; Madzharova: Friedrich Alexander University of Erlangen-Nuremberg, Lange Gasse 20, 90403 Nuremberg, Germany, boryana.madzharova@fau.de; Merella: Università degli Studi di Cagliari and Vysoká škola ekonomická v Praze, W. Churchilla 1938/4, 130 67 Prague 3, Czech Republic, merella@unica.it. The authors gratefully acknowledge the financial support of the Czech Science Foundation under grant No. GA CR 19-16764S for the project “Revisiting the relationship between import quality and importer income and its effects on international trade patterns.”

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, known as the ‘home-market effect,’ states that local demand profiles are 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, does nonhomothetic demand dominate traditional supply-side mechanisms in driving quality specialization? Providing accurate answers to these questions is paramount 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 factor endowments or to local demand conditions.

An essential precondition for the empirical assessment of the above questions is the availability of an accurate method for measuring product quality. Since [Khandelwal’s \(2010\)](#) pioneering contribution, inferring quality from consumer choices has become the standard approach.¹ Yet, the literature following this approach has typically not taken into account how nonhomotheticities alter preferences for quality at different levels of income, hence overlooking the fact that the sets of purchased varieties vary with income. The main reason for this is 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

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

²One 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

This paper uses 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) 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 and enables novel empirical analysis. 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 can explain the estimated quality. Third, it enables the incorporation of 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, and study how production location choices vary with quality at the firm level.

We provide three main contributions to the literature. The first contribution is specific to the literature that follows [Khandelwal \(2010\)](#), which envisions product quality as a demand shifter. We apply this methodology to our dataset and, subsequently, link inferred quality measures to a number of vertical attributes. The estimates show that attributes most clearly associated with vertical differentiation among refrigerators 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 against a large set of attributes that can be vertically ranked.⁴

rely either on cross-country variation of bundles of imports/exports within narrowly defined product categories.

³While the literature following Khandelwal's 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.

⁴By linking inferred quality measures to objective fridge attributes, the paper relates to the very few papers that have so far linked quality to direct objective measures of it. For example, [Crozet, Head and Mayer \(2012\)](#) and [Chen and Juvenal \(2016\)](#) who, relying on experts' assessments, study how product quality can account for differences in export values and prices among French champagne and Argentine

The second contribution is testing for the presence of nonhomothetic preferences along the quality dimension by exploiting variation of market shares of identical models across EU markets. To this end, we borrow the nonhomothetic CES preferences introduced by [Matsuyama \(2019\)](#) and adapt them to a context of vertically differentiated varieties. 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, lending thus support the notion that preferences are non-homothetic. In particular, we show . 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.⁵

The third contribution pertains to location patterns along the quality dimension and how they relate to nonhomothetic preferences. By merging the panel data on sales with information on models' country of origin, we link quality estimates and production location choices. This enables us to assess patterns of vertical specialization at different levels of income per head. We show that higher quality products tend to be produced in richer economies, and that this association is primarily driven by a home-market effect. 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 to differences in factor endowments significantly. These findings add to the evidence presented by [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.

By looking into variation within brands producing in plants located in different countries,

wine producers, respectively; and [Auer, Chaney and Saure \(2018\)](#) who, relying on hedonic price theory applied to several model-specific attributes, create quality categories for European cars. This 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.

⁵Previous evidence of nonhomothetic behavior along the quality dimension has mostly relied on unit values as a proxy of quality (e.g., [Schott \(2004\)](#), [Hallak \(2006\)](#), [Verhoogen \(2008\)](#), [Bastos and Silva \(2010\)](#), [Manova and Zhang \(2012\)](#)). Two recent exceptions can be found in [Piveteau and Smagghue \(2020\)](#) and [Heins \(2020\)](#), who use a log-logit demand structure to allow price elasticities of certain goods to decrease with consumer income and thereby accommodate nonhomothetic demand schedules. However, those papers do not test whether higher-quality products feature greater income demand elasticities. More precisely, they analyze whether price elasticities fall with consumer income, which in their contexts leads to demand patterns consistent with nonhomothetic preferences.

new insights emerge. 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 under [Khandelwal’s \(2010\)](#) approach, 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 \(2015\)](#)).

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 each fridge model’s objective attributes. Section 4 introduces the more general demand-side framework with nonhomothetic CES utility and tests for the presence of nonhomotheticities. 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

We use data on 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.⁶ 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 a 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.⁷

For the purposes of our analysis, a downside of the GfK’s MDA panel for the EU is its limited coverage of products’ attributes.⁸ For this reason, we complement the EU

⁶The EU Member States not in the panel are Bulgaria, Cyprus, Ireland, Luxembourg and Malta.

⁷On 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.

⁸The data set contains three product characteristics, namely: type of installation (built-in or free-standing), a size variable, which combines information on 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

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 manufacturer’s model number.⁹ 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.¹⁰ Thus, the intersecting sample can be augmented with data on models’ country of manufacture (origin).¹¹ 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 of 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 (See Figure A.3 in Appendix A.2 for an example). 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.¹² 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 add bilateral exchange rates expressing a unit of country-of-destination currency in terms of its country-of-origin currency value.

Table 1 shows descriptive statistics of the primary data in Panel A. In Panel B, the analysis of vertical product differentiation.

⁹Even 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 (2020), who study the 2014 devaluation episode, demonstrate changes in quality composition for apparel.

¹⁰The EEU is a customs union (since 2010) and a common market (since 2012) between Armenia, Belarus, Kazakhstan, Kyrgyzstan, and Russia.

¹¹Given that intermediary inputs can be produced in numerous locations, what we likely observe is a country of assembly/export. A detailed explanation of the steps entailed in assembling the country of origin data is provided in Appendix A.2.

¹²In 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.

TABLE 1 – DESCRIPTIVE STATISTICS

	Mean	Standard Deviation	Minimum	Maximum	N
Panel A. Primary Data: Full Sample					
Unit sales	50.52	(158.06)	0	13,096	2,406,880
Price (Euro)	667.40	(478.87)	0.01	16,452	2,522,908
N ^o 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)	0	7,276	1,728,751
Price (Euro)	691.56	(484.28)	0.36	13,284	1,806,850
N ^o 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
N ^o destination countries	11.42	(5.32)	2	23	364,713
N ^o 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 2 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 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 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. N^o destination countries are the average number of countries in which refrigerators are sold. The data consists of 23 destination countries (Russia is excluded), 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 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.

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 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 2012-2013.¹³ Further, single-country products are more likely to be retailer-specific or local brands with limited vertical differentiation.¹⁴ *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.¹⁵

Table 2 provides descriptive statistics of the physical attributes in the data.¹⁶ All in all, the sample exhibits substantial vertical differentiation. 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, side-by-side design, and dispensers are less frequent and occur in 17% and 6% of the sample, respectively. The majority of the refrigerators are assigned an A+ energy label, with very few appliances present in the most efficient A+++ category.

3 Demand Side Analysis

This section borrows the constant elasticity of substitution (CES) demand-side framework presented in [Khandelwal, Schott and Wei \(2013\)](#), and adapts it to a context with representative consumers from several destination countries. 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 nonhomotheticities linked to the quality dimension.

¹³This 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.

¹⁴For example, 17% of single-country products in the data are retailer brands, which are identified by a specific letter in their id number.

¹⁵This would be in line with “shipping the good apples out” effect as discussed, e.g., in [Hummels and Skiba \(2004\)](#).

¹⁶Table A.1 in the Appendix provides an exhaustive list/description of all product characteristics in the data and separates them into vertical, horizontal, or size-related.

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
N ^o 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 percent of each level from total observations. For 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 Demand

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. The consumption aggregator $Y_{i,t}$ bundles *goods* according to a Cobb-Douglas function with sectoral shares $\alpha_s \in (0, 1)$ and, for each good $s \in \mathcal{S}$, it aggregates *varieties* of s according to a CES function with elasticity of substitution across varieties $\sigma_s > 0$. Formally:

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

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 .

Analogously to [Khandelwal et al. \(2013\)](#), we interpret the demand shifter $\lambda_{i,j_s,t}$ as the quality of variety j_s as perceived by country i 's representative household in period t . Henceforth, we assume that $\lambda_{i,j_s,t}$ comprises three separate components, namely

$$\lambda_{i,j_s,t} = \exp(\theta_{j_s} + \varsigma_{i,j_s} + v_{i,j_s,t}). \quad (2)$$

The term ς_{i,j_s} in (2) is a time-invariant taste shifter specific to country i and variety j_s that averages out across countries, i.e. we assume that $E_{\mathcal{I}}(\varsigma_{i,j_s}) = 0$. The term $v_{i,j_s,t}$ is an independent and identically distributed zero-mean taste shock specific to country i , variety j_s and period t , i.e. we assume that $E_{\mathcal{I},\mathcal{J}_{s,t}}(v_{i,j_s,t}) = 0$. 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 consumers' 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:

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

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 $Q_{i,s,t} \equiv \sum_{j_s \in \mathcal{J}_{s,t}} q_{i,j_s,t}$.¹⁷ Taking logarithms of

¹⁷See Appendix [A.1.1.1](#) for a complete derivation of (3).

(3), we obtain the following linear equation:

$$\ln m_{i,j_s,t} = -\sigma_s \ln p_{i,j_s,t} + \mu_{i,t} + \theta_{j_s} + \varsigma_{i,j_s} + v_{i,j_s,t}, \quad (4)$$

where $\mu_{i,t} \equiv -\ln \Omega_{i,t}$. Equation (4) constitutes the starting point of the 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 both θ_j and $\varsigma_{i,j}$, equation (4) can be re-written as:

$$\ln m_{i,j,t} = -\sigma \ln p_{i,j,t} + \mu_{i,t} + \phi_{i,j} + v_{i,j,t}, \quad (5)$$

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, 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. The country(destination)-date fixed effects $\mu_{i,t}$ account for time-varying country-specific shocks that are constant across models and accommodate the possibility of a differential impact of common shocks across countries within a month-year. Thus, they capture destination-specific seasonality for each year 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 the regression, 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 pioneered by [Khandelwal \(2010\)](#). The intuition of this method is that conditional on price, higher quality products command larger market shares. Quality is thus the residual of a demand function, which, in the above specification, could be backed out by averaging the sum of the estimated country-model fixed effects and residuals across countries and over time. Formally:

$$\hat{\theta}_j = \frac{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \hat{\phi}_{i,j} + \hat{v}_{i,j,t}}{NT}, \quad (6)$$

where N denotes the number of countries, \mathcal{T} the time interval, 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 likely induces positive correlation between $v_{i,j,t}$ and price, and would therefore lead to a biased and inconsistent OLS estimate of σ .¹⁸ 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 $\hat{\theta}_j$ as well.

To deal with price endogeneity, we exploit the fact that we are able to trace the country of origin c where the plant producing model j is located. Provided that changes in bilateral exchange rates over time, $ER_{c,i,t}$, are at least partly passed through into consumer prices, they can serve as a source of exogenous variation in retail prices in destination markets i .¹⁹ Note that in the current framework, ideally, an instrumental strategy would rely on model-specific cost shifters to identify model-specific price variation. Within a 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 locations within a year. Nevertheless, some models are manufactured domestically, i.e. $c = i$, 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 the instrument does not vary, since model j 's country of origin is constant over time.

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

$$\ln p_{i,j,t} = \beta \ln ER_{c,i,t} + \delta_{i,j} + \tau_{i,t} + \varepsilon_{i,j,t}, \quad (7)$$

¹⁸For 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.

¹⁹Similarly, [Piveteau and Smagghue \(2019\)](#) make use of the different set of countries a firm imports from and the different share of country-specific imports in the firm's operating costs 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 c , then an increase in $ER_{c,i,t}$, indicating depreciation of c 's currency makes c 's goods sold in markets 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 $ER_{c,i,t}$ is remote. Such a threat to the exogeneity of the instrument would require demand in country i for refrigerators produced in country c 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 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, price elasticity estimates would be biased towards zero. This is confirmed in Column (1), which reports a simple OLS estimation that yields a demand curve with an elasticity of 0.59.²⁰ 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 gradual adjustment of retail prices to exchange rates. The 2SLS estimation results in a substantially larger price elasticity of 3.85, which is precisely estimated. Given the first-stage results, which show that neither the contemporaneous, nor the first two lags of ER are statistically significant, the Sanderson-Windmeijer F-statistic is understandably relatively low at 12.08, as only the third lag significantly explains prices. In fact, an exactly identified specification shown in Column (3) results in a similar price response, but exhibits a four-fold increase in the F-statistic and a larger σ of 4.75.²¹ Limiting the sample to models whose destination-

²⁰Without the inclusion of brand-year fixed effects, the OLS estimate of σ is positive and statistically significant implying an upward-sloping demand.

²¹It 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, and thus possibly improve the efficiency of the first stage estimation, 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+++ in light of the discussion in Section 2 linking low energy consumption to the presence of high quality attributes, such as inverter compressor, low decibel

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 (0.025)**	-3.851 (1.308)***	-4.753 (1.420)**	-6.090 (1.851)***	-4.753 (2.193)** [0.004]***	-6.090 (2.510)** [0.000]***
	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 (0.016)***	-0.045 (0.007)***	-0.039 (0.007)***	-0.045 (0.014)***	-0.039 (0.012)***
F-statistic		12.08	46.28	31.98	11.22	9.77
p-value		0.000	0.000	0.000	0.003	0.005
Destination-date	Yes	Yes	Yes	Yes	Yes	Yes
Product-destin.	Yes	Yes	Yes	Yes	Yes	Yes
Brand-year	Yes	Yes	Yes	Yes	Yes	Yes
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 a country where a model is sold (destination) and the country of its manufacture (origin). 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). Wild-cluster bootstrapped p-values clustering by country are shown in brackets in Columns (5)-(6). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

origin country pair is such that the instrument varies over time in Column (4) leads to a higher price elasticity of 6.1.

The estimate of the exchange rate pass-through into retail prices reported in Panel B is between 4% and 5%, and is consistent with 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 micro data 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 and adjustment costs explain the very limited pass-through by retailers. At the second stage, the price elasticity in our preferred specification in Column (3) is within the estimate range of structural demand side models based on product-level data on market shares and prices. This literature generally obtain elasticities well above 2 (e.g. [Piveteau and Smagghue, 2019](#); [Goldberg and Hellerstein, 2013](#); [Nakamura and Zerom, 2010](#); [Broda and Weinstein, 2006](#)). Our 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 refrigerators and freezers (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 in effect 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. The next two columns, therefore, 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. Although the F-statistics are lower and approach the Staiger-Stock threshold for weak instruments in the case of exactly identified models, both the pass-through effect and the price elasticity σ remain highly statistically significant.

The cluster-robust variance estimator is sensitive to few and heterogeneous clusters. Even though the literature does not offer a clear-cut definition of what number constitutes 'too few' clusters, with 23 countries in the data, which are moderately unbalanced (see note to Table 1), optimally we should perform the wild-cluster bootstrap, which provides reliable statistical inference even in the presence of small number of clusters with unequal number of observations (e.g. [MacKinnon and Webb, 2017](#); [Cameron and Miller, 2015](#)). The p-values from a wild-cluster bootstrap reported in Columns (5) and (6) of Table 3

range, and others. Neither of the interaction terms prove statistically significant, as shown in Table A.2 in the Appendix. An interaction of the IV with an indicator for top-level brands (not reported) also did not point to the presence of heterogeneity.

TABLE 4 – PLACEBO TEST: RANDOM ASSIGNMENT OF COUNTRY OF ORIGIN

	Sign		p-value ≤ 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 $\ln(\text{Price})$			
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 $\ln(\text{Price})$ 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.

demonstrate that statistical inference is not compromised.

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.

TABLE 5 – DETERMINANTS OF INFERRED QUALITY

	Inferred Quality					log(Price)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Energy label	0.135 (0.026)***			0.217 (0.030)***	0.222 (0.030)***		
A+++		0.599 (0.137)***				0.145 (0.063)**	0.243 (0.071)***
A++		0.313 (0.114)***				0.017 (0.066)	0.160 (0.072)**
A+		0.153 (0.099)				-0.045 (0.046)	0.020 (0.047)
A		0.067 (0.087)				-0.048 (0.040)	-0.044 (0.042)
ln(kWh)			-0.047 (0.100)				
Zero-degree box	0.345 (0.145)**	0.342 (0.144)**	0.379 (0.165)**	0.323 (0.096)***	0.322 (0.098)***	0.214 (0.094)**	0.207 (0.056)***
Freezer side	0.811 (0.058)***	0.814 (0.061)***	0.864 (0.068)***	0.845 (0.065)***	0.847 (0.060)***	0.549 (0.052)***	0.529 (0.035)***
Dispenser	0.242 (0.077)***	0.245 (0.077)***	0.189 (0.097)*	0.287 (0.060)***	0.269 (0.058)***	0.120 (0.063)*	0.157 (0.037)***
No-frost system	0.282 (0.102)***	0.276 (0.098)***	0.364 (0.103)***	0.275 (0.076)***	0.275 (0.079)***	0.224 (0.049)***	0.213 (0.036)***
ln(Noise Level)	-1.474 (0.623)**	-1.433 (0.616)**	-2.594 (0.711)***	-1.572 (0.566)**	-1.538 (0.573)**	-0.454 (0.338)	-0.827 (0.305)**
Display	0.223 (0.026)***	0.222 (0.026)***	0.233 (0.030)***	0.197 (0.034)***	0.195 (0.034)***	0.202 (0.026)***	0.173 (0.028)***
Metal exterior	0.099 (0.038)**	0.101 (0.038)**	0.105 (0.038)**	0.134 (0.045)***	0.133 (0.045)***	0.054 (0.015)***	0.105 (0.024)***
N ^o doors	0.391 (0.048)***	0.395 (0.048)***	0.338 (0.046)***	0.360 (0.050)***	0.368 (0.050)***	0.198 (0.041)***	0.159 (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, $\hat{\theta}_j = (\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \ln m_{i,j,t} + \hat{\sigma}_{2SLS} \ln p_{i,j,t} - \hat{\mu}_{i,t}) / (NT)$, in columns (1)-(3), and $\hat{\theta}_{ijt} = \ln m_{i,j,t} + \hat{\sigma}_{2SLS} \ln p_{i,j,t} - \hat{\mu}_{i,t}$ 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 the cross-section of products. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 of the decomposition 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. Adapting (6) to the 2SLS framework, the quality of model j is inferred from the following expression:

$$\widehat{\theta}_j = \frac{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \ln m_{i,j,t} + \widehat{\sigma}_{2SLS} \ln p_{i,j,t} - \widehat{\mu}_{i,t}}{NT}, \quad (8)$$

where $\widehat{\sigma}_{2SLS}$ denotes the two-stage least square estimate of the price elasticity and $\widehat{\mu}_{i,t}$ stand for the estimated country-date fixed effects. For the 2,069 products that enter the estimation the index is close to normally distributed as shown in Figure A.2.

To explore the relationship between estimated quality and product features, we standardize $\widehat{\theta}_j$ and employ the following specification:

$$\widehat{\theta}_j = b_j + \sum_{k=1}^n \alpha_k x_{kj} + \epsilon_j, \quad (9)$$

where b_j is a brand fixed effect.²² α_k captures the effect of the k th attribute x_{kj} 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 these characteristics, we focus on the number of doors as a single size indicator. With the exception of noise, we expect a positive correlation between a feature availability and $\widehat{\theta}_j$ such that $\alpha_k > 0$. 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 the cross-section of models according to (8), and show OLS estimates with brand fixed effects. Columns (4) to (5) use instead as dependent variable $\widehat{\theta}_{ijt} = \ln m_{i,j,t} + \widehat{\sigma}_{2SLS} \ln p_{i,j,t} - \widehat{\mu}_{i,t}$. In these two cases, we incorporate

²²In the following sections, we compare the performance of $\widehat{\theta}_j$ to that of a quality measure estimated under the assumption of non-homothetic preferences. Such a comparison necessitates the standardization of both measures, which is why we prefer to standardize at this point.

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, noise and number of doors 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, which consumers would perceive to enhance (reduce) quality are found to be positively (negatively) correlated with the dependent variable. Adding one more door to a refrigerator increases the index by 0.4, while a 1% rise in the noise level leads to a 0.02 reduction in the quality measure.

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 will still likely rate 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 cross-section, 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. Comparing the parameter estimates of Columns (2) and (6), some important qualitative differences emerge. High energy efficiency, for example, exerts a significant and economically meaningful effect on the quality measure, which is, however, absent in the aggregated hedonic specification. Similarly, the effects of noise and the availability of an automated defrosting system on the price are not different from zero. Nevertheless, Column (7) demonstrates that the estimated relationships in a hedonic setting are much more sensitive to the level of aggregation than the inferred quality measures.

Besides gauging the impact of different attributes on quality, the results in Table 5 convey two general important and related messages. 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 used to infer those measures 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, which 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. Given choices by representative consumers across destination markets with wide income disparities, allowing for nonhomotheticities along the quality dimension seems an important concern to take into account.²³

This section expands the standard CES framework used in Section 3 to accommodate nonhomothetic preferences. To do so, we borrow the nonhomothetic CES preference specification formulated by Matsuyama (2019), and adapt it to a framework with vertically differentiated varieties.²⁴ Formally, let the consumption aggregator $Y_{i,t}$ be implicitly defined through the following expression:

$$\prod_{s \in \mathcal{S}} \left[\left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{\frac{\sigma_s}{\sigma_s - 1}} \right]^{\alpha_s} = 1. \quad (10)$$

As in Section 3, let $\lambda_{i,j_s,t} \equiv \exp(\theta_{j_s} + \varsigma_{i,j_s} + v_{i,j_s,t})$ in (10) be a demand shifter specific to country i , variety j_s , and period t . The variable $q_{i,j_s,t}$ denotes again the quantity consumed of variety j_s in country i in period t . The distinctive feature of (10), relative to the CES utility function in (1), is the presence of the variety-specific parameters ε_{j_s} , which govern the income elasticity of variety j_s .²⁵

Matsuyama (2019) shows that the term $Y^{(\varepsilon_{j_s} - \sigma_s)/\sigma_s}$ in (10) yields well-defined income

²³Evidence consistent with nonhomotheticities along the quality dimension has been recurrently presented in the literature, chiefly by studies showing that richer importers tend to buy varieties of goods exhibiting higher 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).

²⁴Matsuyama (2019) exploits the isoelastically nonhomothetic CES preferences to accommodate heterogeneous income elasticities across sectors. The utility function in (10) 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.

²⁵Note that (1) is actually a special case of (10), which obtains from setting $\varepsilon_{j_s} = 1$ for all j_s and solving the resulting expression for $Y_{i,t}$ – see Appendix A.1.1.2 for a formalization of this argument.

effects on demand. 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 ε_j to the intrinsic quality term associated with variety j . (Given that the empirical analysis focuses solely on the refrigerators industry, once again we henceforth drop the s subscript to ease notation.) In particular, let

$$\varepsilon_j = \kappa(\theta_j), \quad (11)$$

where $\kappa(\cdot)$ is assumed to be a monotonic function either strictly increasing, decreasing, or constant with respect to θ_j . The presence of nonhomotheticities would thus materialise as $\kappa'(\cdot) > 0$.²⁶

When preferences are given by (10), the optimization problem of country i 's representative agent (in period t) yields the following quantitative market shares:

$$m_{i,j,t} \equiv \frac{q_{i,j,t}}{Q_{i,t}} = p_{i,j,t}^{-\sigma} e^{\theta_j + \varsigma_{i,j} + v_{i,j,t}} Y_{i,t}^{\varepsilon_j} \tilde{\Omega}_{i,t}, \quad (12)$$

where $\tilde{\Omega}_{i,t} \equiv \left(\sum_{j \in \mathcal{J}_t} p_{i,j,t}^{-\sigma} Y_{i,t}^{\varepsilon_j} \lambda_{i,j,t} \right)^{-1}$, and $Q_{i,t} \equiv \sum_{j \in \mathcal{J}_t} q_{i,j,t}$ is the aggregate consumption across all varieties j in country i in period t . Applying logarithms to (12), we obtain

$$\ln m_{i,j,t} = -\sigma \ln p_{i,j,t} + \varepsilon_j \ln Y_{i,t} + \tilde{\mu}_{i,t} + \theta_j + \varsigma_{i,j} + v_{i,j,t}, \quad (13)$$

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

The main difference between (13) and (4) lies in the fact that the former includes one additional term, $\varepsilon_j \ln(Y_{i,t})$, which captures the impact of variety j 's income elasticity (ε_j) on its (log) market share. Notice that when $\varepsilon_j = 1$ for all $j \in \mathcal{J}_t$, the expression in (13) boils down to (4).²⁷ In other words, the demand structure stemming from the homothetic CES utility function represents a *special* case of the one derived from (10), when income elasticities are identical and equal to one for all j .

4.1 Testing for the Presence of Nonhomotheticities

Combining (13) and (11), we could now test whether the demand schedules for refrigerators seem to exhibit a non-homothetic behaviour along the quality dimension. In order

²⁶Nonhomotheticities would also be present if $\kappa'(\cdot) < 0$. This would, however, imply that willingness to pay for quality *decreases* with income, which is at odds with the empirical evidence to date.

²⁷To see this formally, note that when $\varepsilon_j = 1$ for all $j \in \mathcal{J}_t$, then $\tilde{\Omega}_{i,t} = Y_{i,t}^{-1} \left(\sum_{j \in \mathcal{J}_t} p_{i,j,t}^{-\sigma} \lambda_{i,j,t} \right)^{-1}$, and hence $\tilde{\mu}_{i,t} = -\ln \tilde{\Omega}_{i,t} = \mu_{i,t} - \ln(Y_{i,t})$. Plugging this into (13), and cancelling out repeated terms, yields the exact same expression as in (4).

to approach this question empirically, we further simplify (11), by assuming a linear relationship between ε_j and θ_j ; namely, $\varepsilon_j = \kappa \cdot \theta_j$. Replacing $\varepsilon_j = \kappa \cdot \theta_j$ into (13), and bearing in mind again that we can only identify empirically $\phi_{i,j} \equiv \theta_j + \varsigma_{i,j}$ by means of country-model fixed effects, we obtain:²⁸

$$\ln m_{i,j,t} = -\sigma \ln p_{i,j,t} + \kappa (\theta_j \times \ln Y_{i,t}) + \tilde{\mu}_{i,t} + \phi_{i,j} + v_{i,j,t}. \quad (14)$$

We use regression equation (14) to test whether the assumption of homothetic preferences along the quality dimension finds empirical support. Notice that if consumers' preferences *were* actually 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 (14) associated to the interaction term $\theta_j \times \ln Y_{i,t}$ not being statistically different from zero.²⁹

Table 6 displays in column (1) the estimation results of (14) interacting $\ln Y_{i,t}$ –measured by country i 's log-income per capita (in PPP)– with θ_j measured using $\hat{\theta}_j$ given by (6) in Section 3. (The regression is, again, carried out by 2SLS instrumenting $\ln p_{i,j,t}$ with (log) bilateral exchange rates, and it also includes brand-year fixed effects to be consistent with our benchmark specification in Table 3.) The estimates in column (1) report two sets of standard errors: i) robust standard errors clustered at the country level in parenthesis; ii) bootstrapped standard errors clustered at the country level in squared-brackets.³⁰ Our main coefficient of interest in this column is the parameter associated to the interaction term, κ . As we can observe, the estimate $\hat{\kappa}$ is positive and highly significant. This implies that higher-quality fridge models (i.e., those exhibiting a larger $\hat{\theta}_j$) tend to command relatively greater market shares in richer destination countries. Concerning the estimated price elasticity ($\hat{\sigma}$), this remains negative and significant (albeit with a p-value slightly above 5%), while its point estimate is quantitatively similar to that one in Table 3.

The positive and highly significant estimated κ in column (1) clashes with the notion of demand homotheticity, suggesting instead the presence of nonhomothetic preferences along the quality dimension. From that perspective, the positive estimate for κ in (14) raises a flag on the accuracy of the homothetic preference specification assumed throughout Sec-

²⁸As robustness, we used also a fourth order polynomial expression for $\varepsilon_j = \kappa(\theta_j)$ interacted with log-income. The results, which are available from the authors upon request, yield a positive and significant estimate only for the linear term, and whose point estimate is quite similar to that one displayed in column (1) of Table 6.

²⁹More precisely, under the null hypothesis that preferences are represented by (1), the regression equation (14) should yield an estimate of κ that is not significantly different from zero when using the 2SLS estimates $\hat{\theta}_j$ obtained in Section 3 to measure model j 's quality as done in column (1).

³⁰We compute bootstrapped clustered standard errors as well, given that $\hat{\theta}_j$ is the result of a previous estimation procedure.

TABLE 6 – TESTING FOR NON-HOMOTHETIC PREFERENCES

	(1)	(2)	(3)
Quality measure:	Homothetic	Non-homothetic	
		1st Step	2nd Step
log(Price)	-5.273 (2.305)** [2.802]*	-5.533 (2.383)**	-3.462 [3.250]
$\hat{\theta}_j \times \ln(Y)$	1.831 (0.478)*** [0.520]***		
$\hat{\theta}_j^{nh} \times \ln(Y)$			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 table reports results from the estimation of eq. (14), and the two steps involved in the estimation of eq. (16) shown separately in Columns (2) and (3). In Column (1), income 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

tion 3. In particular, those preferences seem to be missing some degree of heterogeneity in the response by 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

Our previous results suggest that inferring quality measures from a standard homothetic CES utility function risks overlooking some important degree of heterogeneity in consumers' behaviour stemming from income variations. In that respect, column (1) can be legitimately interpreted as testing whether or not homothetic preferences are indeed an accurate representation of consumer behaviour. However, if preferences are actually *nonhomothetic*, the inferred quality estimates used when carrying out the regression equation in column (1) will be based on an *inaccurate* specification of consumer behaviour. In particular, if preferences are represented by (10) with (11), 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 market shares.

Columns (2) and (3) of Table 6 aim at taking into account the impact of income effects when inferring quality from quantitative market shares. 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 4, plus some additional unobserved component on top of those attributes. That is, we let

$$\theta_j = \sum_{k=1}^9 \alpha_k \cdot z_{kj} + \vartheta_j, \quad (15)$$

where each z_{kj} summarises attribute k in model j (e.g., its the level of energy efficiency, whether or not it has a no-frost system, the level of noise, etc.) and ϑ_j captures the additional unobserved determinants of quality.

Based on equation (15), we could re-write the regression equation (14) as follows:

$$\ln m_{i,j,t} = -\sigma \ln p_{i,j,t} + \sum_{k=1}^9 \tau_k \cdot (z_{kj} \times \ln Y_{i,t}) + \tilde{\mu}_{i,t} + \phi_{i,j} + v_{i,j,t}, \quad (16)$$

where $\tau_k \equiv \kappa \cdot \alpha_k$.³¹ Compared to (14), equation (16) includes a set of nine interaction terms between models' attributes (z_{kj}) and log income per head.

Column (2) in Table 6 displays the estimated $\hat{\sigma}$ based on the 2SLS estimation of (16). (In order not to clutter the table we avoid reporting the nine estimates for the interaction terms.) Unlike the estimated price elasticity in column (1), the one reported in column

³¹Note that the error term $v_{i,j,t}$ includes the period-specific deviations of the interaction term between the unobserved quality component ϑ_j and $\ln Y_{i,t}$.

(2) aims at taking into account the effects of nonhomotheticities by including in the estimation the set of interaction terms $z_{kj} \times \ln Y_{i,t}$ as "stand-ins" for θ_j in (14).³²

The first step carried out in column (2) allows estimating the price elasticity while also (approximately) accounting for the impact of the nonhomothetic term $\theta_j \times \ln Y_{i,t}$ in (16). However, given that the parameters τ_k are each the result of a product ($\kappa \cdot \alpha_k$), the estimates $\widehat{\tau}_k$ are not able to identify κ and each α_k separately. Hence, to obtain an estimated value of κ that accounts for nonhomotheticities when measuring θ_j , in a second step we rely on the estimated $\{\widehat{\tau}_k\}_{1,\dots,9}$ through (16), alongside the corresponding residuals $\widehat{\phi}_{i,j}$ and $\widehat{v}_{i,j,t}$. Based on those estimates, we next compute inferred quality measures accounting for nonhomothetic behaviour by consumers, averaging across i and t analogously as done in (6). Namely,

$$\widehat{\theta}_j^{nh} = \frac{\sum_{i \in \mathcal{I}} \sum_{t \in \mathcal{T}} \left[\left(\sum_{k=1}^9 \widehat{\tau}_k \cdot z_{kj} \right) \times \ln Y_{i,t} + \widehat{\phi}_{i,j} + \widehat{v}_{i,j,t} \right]}{N \times T}. \quad (17)$$

In column (3) we display the results of the 2SLS estimation of (14) when using $\widehat{\theta}_j^{nh}$, as given by (17), to measure θ_j . The main advantage of this is that, when using $\widehat{\theta}_j^{nh}$, we avoid relying on residual market shares obtained from the homothetic log-market shares regression equation (4). As such, provided the term $\sum_{k=1}^9 \alpha_k \cdot z_{kj}$ manages to capture a substantial amount of variation in intrinsic quality across models, we are able to incorporate income effects into the residual market shares (i.e., the market shares after cleaning out the effect of prices).³³

The estimate $\widehat{\kappa}$ displayed in column (3) κ remains positive and highly significant. (The standard errors reported in squared-brackets are bootstrapped and clustered at the country level to take into account that $\widehat{\theta}_j^{nh}$ results from a previous estimation.) It can also be noticed that the point estimate increases quite significantly in column (1) relative to the other two columns.³⁴ This means that the income elasticity of quality is severely underestimated when preferences are assumed to be homothetic. One possible reason behind this bias could be related to measurement error in column (1). The estimated

³²Relative to the point estimate in Table 3, the price elasticity in Table 6 rises slightly. A downwards bias in the magnitude 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 taking into account the impact of nonhomothetic preferences along the quality dimension would lead to a downwards bias in the estimated price elasticity.

³³One alternative would be not to run again (14) by 2SLS using $\widehat{\theta}_j^{nh}$ to measure θ_j , but directly subtracting the price effect to 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 $\widehat{\sigma} = 5.533$.

³⁴The interaction term estimates in Table 6 are directly comparable in terms of magnitude, as the inferred quality measures have all been standardized.

inferred qualities $\widehat{\theta}_j$ are based on the assumption of homothetic preferences. As a result, if preferences are actually nonhomothetic, the estimates $\widehat{\theta}_j$ would suffer from measurement error, possibly leading to a downwards bias in the estimate of κ in column (1).³⁵

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 address these two questions.

Regarding the first question, Figure 1 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 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 accounting for income effects via nonhomothetic preferences.³⁶

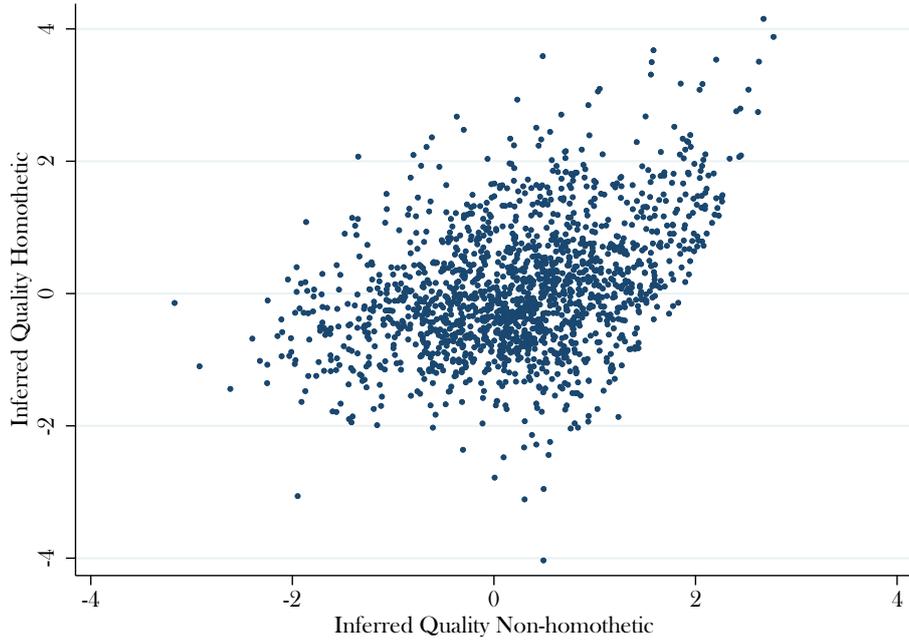
This expectation is confirmed in Table A.3 in Appendix A.1.2, which compares the parameter estimates of different attributes on the inferred quality measures in the case of homothetic and nonhomothetic preferences.³⁷ The most striking result in Table A.3 is the substantial rise in the importance of energy efficiency as a determinant of quality.

³⁵Although we also report the estimated value of the price elasticity in column (3), this estimate should be deemed as less reliable than that one reported in column (2). As mentioned above in the text, the only reason why we need to estimate column (3) is because column (2) is unable to identify κ and each α_k separately. Nevertheless, column (2) is sufficient to identify the price elasticity σ .

³⁶If fridge models could be cleanly ex-ante ordered by virtue of their vertical attributes, one would not expect to see much ranking 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.

³⁷Note that the estimates are directly comparable since quality measures are standardized.

FIGURE 1 – QUALITY MEASURES CORRELATION

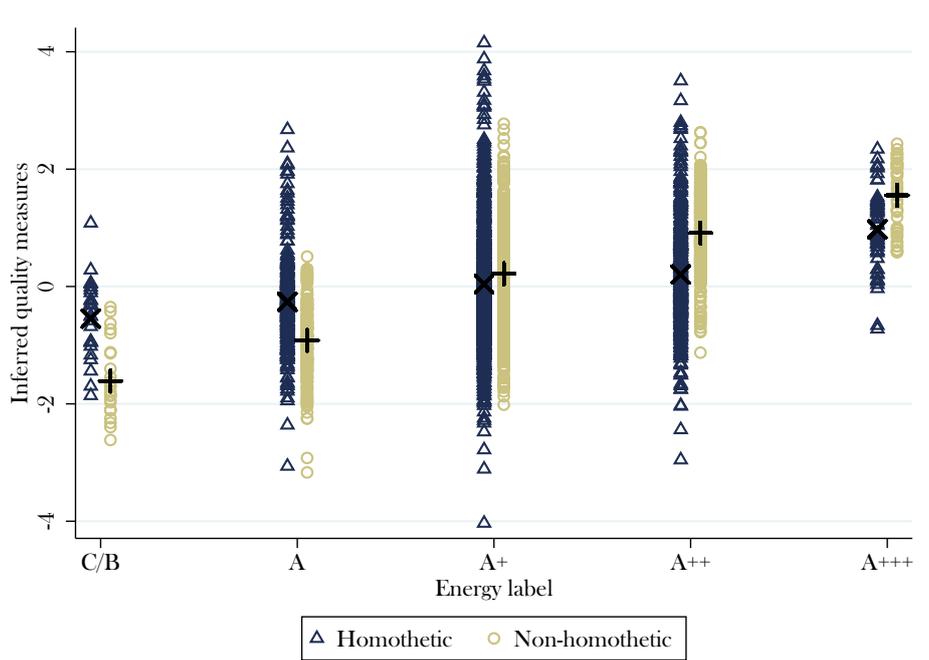


Note: The scatter plot correlates the quality measures under homothetic and nonhomothetic preferences for each of the models in the sample.

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.

Figure 2 provides a visual description of how the importance of energy efficiency at determining quality varies when accounting for nonhomotheticities. The horizontal axis orders 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 high energy efficiency models A++ and A+++, the opposite occurs: high energy efficiency models tend to receive higher quality rating under the nonhomothetic CES than under homothetic CES. An important message from Figure 2 is that being able to produce greener fridges with high energy efficiency may be crucial for attracting richer consumers. Not accounting for the variation in 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

FIGURE 2 – QUALITY MEASURES AND ENERGY EFFICIENCY



Note: 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).

in richer markets and the factors that maximize market penetration. Furthermore, the implications of this result potentially extend far beyond the refrigerator industry: almost all household appliances in the EU are subject to analogous labelling requirements.

5 Supply-Side Analysis: Choice of Production Location

This section explores production location choices for varieties in a setting with multi-plant producers. The main goal is to check if location decisions by firms vary with the level of quality of a given variety. In particular, we investigate whether there is a connection between the intrinsic quality of a refrigerator 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 nonhomothetic preferences, firms may seek to manufacture a product in a country, where local demand for it is greater.³⁸ The analysis in Section 4 reveals that demand for higher-quality refrigerators tends to be proportionally stronger in richer

³⁸This 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.

countries. Costs arising from geographic barriers may then prompt firms to locate the production of specific models in countries where their quality best matches domestic households' (income-dependent) preferences. Given the findings in Section 4, we expect to find 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 depend on traditional relative productivity considerations: production occurs where it is most cost-efficient to do so. Specifically, with regard to quality differentiation, it can be argued that manufacturing more sophisticated models requires a more productive environment, possibly featuring higher levels of human or physical capital, or easier access to financial markets.

Section 5.1 develops a stylized framework to illustrate the emergence of the 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 exercises, whose findings are reported in Section 5.2.

5.1 Optimal Location Choice with a Home-Market Effect

Consider a profit-maximising firm that is facing the decision of where to locate the production line for a generic fridge model j . Let model j be characterised 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.34) in Appendix A.1.1.2, and assume that the demand shifters $\lambda_{i,j}$ do not vary at the destination country level, i.e., $\lambda_{i,j} = \lambda_j$.³⁹ Finally, throughout this subsection, we refer to the quality level of model j as the monotonic transformation $\lambda_j = \exp(\theta_j)$.⁴⁰ Under these assumptions, the demand function for model j in country i becomes:

$$q_{i,j} = \Omega_i \lambda_j p_{i,j}^{-\sigma} Y_i^{\tilde{\kappa}(\lambda_j)}, \quad (18)$$

where $\tilde{\kappa}(\lambda_j) \equiv \kappa(\ln \lambda_j)$, and Ω_i collects quantities that are unresponsive to variations in λ_j .⁴¹

Suppose that the firm can locate the production of model j in either of two countries, h and l . 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

³⁹This simplifying assumption, along with all subsequent ones in this subsection, could be dispensed with, albeit at the cost of substantially heavier algebraic expressions.

⁴⁰We revert back to $\theta_j = \ln(\lambda_j)$ in the empirical analysis that follows.

⁴¹Formally, $\Omega_i \equiv \alpha P_i^\sigma \left(\sum_{j \in \mathcal{J}} \lambda_j e^{\frac{1}{\sigma} \tilde{\kappa}(\lambda_j) - \sigma} q_{i,j}^{\frac{\sigma-1}{\sigma}} \right)^{-\sigma}$.

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 (18), the price that the firm optimally charges in country i when model j is produced in country k is:

$$p_{i,j}^k = \tau_{k,i} c_{k,j} \sigma / (\sigma - 1), \quad (19)$$

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:

$$\Pi_{i,j}^k = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} \frac{\Omega_i \lambda_j Y_i^{\tilde{\kappa}(\lambda_j)}}{(\tau_{k,i} c_{k,j})^{\sigma-1}}, \quad (20)$$

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

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:

$$\Pi_j^k = \frac{(\sigma - 1)^{\sigma-1}}{\sigma^\sigma} \frac{\lambda_j}{c_{k,j}^{\sigma-1}} \left[\frac{\Omega_h Y_h^{\tilde{\kappa}(\lambda_j)}}{\tau_{k,h}^{\sigma-1}} + \frac{\Omega_l Y_l^{\tilde{\kappa}(\lambda_j)}}{\tau_{k,l}^{\sigma-1}} \right]. \quad (21)$$

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:

$$\varpi_j \equiv \frac{\Pi_j^h}{\Pi_j^l} = \left(\frac{c_{l,j}}{c_{h,j}} \right)^{\sigma-1} \Gamma(\lambda_j), \quad (22)$$

where $\Gamma(\lambda_j) \equiv [\tau^{\sigma-1} \Omega_h Y_h^{\tilde{\kappa}(\lambda_j)} + \Omega_l] / [\Omega_h Y_h^{\tilde{\kappa}(\lambda_j)} + \tau^{\sigma-1} \Omega_l]$ captures the role played by cross-country income differentials in determining whether it is more profitable to locate production in h or l . Given that $\tau \geq 1$, clearly $\Gamma(\lambda_j) > 0$. 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 formalise 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 nonhomotheticities along the quality dimen-

sion, profits earned 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 where higher-quality models tend to be predominantly produced in the richer country.

In order to account for other factors potentially leading to 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 \(2002\)](#). We assume that $c_{k,j} = \omega_k/\zeta_{k,j}$, where $\zeta_{k,j}$ measures labour productivity in terms of model j in country k . Each $\zeta_{k,j}$ is drawn from a Fréchet probability distribution with location parameter $T_{k,j}$ and shape parameter equal to one. The cumulative distribution function reads:

$$F_{k,j}(\zeta) = \exp(-T_{k,j}\zeta^{-1}). \quad (23)$$

We let $T_{k,j} = T - \lambda_j + \psi A_k$, with $\psi \geq 0$ and $T > 0$ be sufficiently large, so that $T_{k,j} > 0$ holds for all λ_j and A_k . A_k can be interpreted as a “stand-in” for a number of factor endowments specific to country k such as the availability of human and physical capital, and the level of financial development. 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 two 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 , smaller factor endowment may necessitate larger labor unit requirements ($\partial T_{k,j}/\partial A_k \geq 0$).

Using $c_{k,j} = \omega_k/\zeta_{k,j}$ jointly with (22) yields:

$$\varpi_j > 1 \quad \Leftrightarrow \quad \zeta_{h,j} > \zeta_{l,j} \Gamma(\lambda_j)^{-\frac{1}{\sigma-1}} \omega. \quad (24)$$

Combining (24) with (23), gives the probability that model j is produced in country h :

$$\Pr_j^h = \frac{1}{1 + \frac{1}{\Psi(\lambda_j)} \frac{1}{\Gamma(\lambda_j)^{\frac{1}{\sigma-1}}} \omega}, \quad (25)$$

where $\Psi(\lambda_j) \equiv (T - \lambda_j + \psi A_h) / (T - \lambda_j + \psi A_l)$. Note that $\Psi'(\lambda_j) \geq 0$, with strict inequality if $\psi > 0$. The latter statement 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 specialization betweenhand lare determined by a home-market effect and a factor-endowment effect. In particular:*

1. *If $\psi = 0$, quality specialization is solely driven by the home-market effect: 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 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 $\hat{\theta}_j$ derived in Section 4 as a dependent variable. As regressors, we include per capita income, as well as a number of supply-side factors whose impact on specialisation in our model is captured by the country-specific variable A_k . In particular, we consider measures of human capital, physical capital per worker, and an indicator of financial market accessibility in the country of origin of each model j .⁴² Notice that since each model is produced in a single location throughout its whole market life, we abstract from the time dimension of the panel data. Given the life-cycle of model j , which is measured from the first year j enters the market of any country in the data, until the last year it exists any country, income per capita $y_{k,j} \equiv \ln(Y_{k,j})$ and factor endowments $A_{k,j}$ are country-of-origin and model-specific time aggregates over the life-cycle of the product.⁴³

⁴²We rely on (i) the per capita GDP in PPP from the Penn World Tables to measure households' income; (ii) the ratio of total private credit to GDP as a measure of financial development; (iii) the human capital index and (iv) the physical capital stock, both taken from the Penn World Tables to measure factor abundance.

⁴³All 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 – QUALITY AND PRODUCTION LOCATION

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			$\hat{\theta}_j^{nh}$			
log(GDP p.c.)	0.595 (0.181)***	0.477 (0.266)*	0.836 (0.479)*	0.508 (0.165)***	0.423 (0.114)***	0.428 (0.112)***
Human Capital Index		0.017 (0.281)				
log(Physical Capital Stock p.c.)			-0.184 (0.354)			
log(Financial Development Index)				0.170 (0.041)***		0.032 (0.035)
Brand	No	No	No	No	Yes	Yes
R ²	2,069	1,983	2,069	2,068	2,068	2,067
N	0.071	0.048	0.074	0.100	0.281	0.286

Notes: The dependent variable is the estimate of inferred quality obtained from estimation of eq (17) under the assumption of non-homothetic preferences. Log per capita GDP, human capital index and log per capita physical capital stock are retrieved from the Penn World Tables, and financial development index—from the World Bank Database. Standard errors in parentheses are robust in all specifications and clustered by brand. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Formally, we consider the following specification:

$$\hat{\theta}_j = \gamma y_{k,j} + \eta A_{k,j} + \varepsilon_j, \quad (26)$$

where γ and η are the main parameters of interest. Following the above discussion, $\gamma > 0$ would suggest the presence of a home-market effect, while $\eta > 0$ would reflect quality specialization driven by factor-endowment effects.

Table 7 illustrates the findings for a number of different regression specifications of equation (26), each one varying in terms of the supply-side variable represented by $A_{k,j}$.⁴⁴ We proceed to include only one supply-side variable at a time given the strong correlation between them. In Column (1) presents the results obtained from the estimation of (26) when only the log of per capita GDP is included as a regressor. This regression intends to capture the impact of income on the production location choice across models differing in quality, as suggested by Lemma 1, disregarding the other factors that may influence relative productivity in higher-quality models. The estimated value for the coefficient associated income per capita is positive and highly significant: that is, richer countries tend to attract the production of higher-quality fridges. This results is in principle consistent with the presence of a home-market effect, as illustrated by Proposition 1 in the

⁴⁴As a robustness check, Table A.4 in Appendix A.1.2 reports the results obtained by using the inferred quality measures produced in Section 3 under a homothetic specification of preferences.

last subsection.

The simple correlation between (log) income per capita and quality of production displayed in column (1) could be simply be capturing the association between quality specialization and other factor endowments that are in turn correlated with income, as posited by case 2 of Proposition 1. In columns (2), (3) and (4) we subsequently add measures of the three above-mentioned supply-side factors to assess their own impact on quality specialization, and whether the impact of income per capita survives their inclusion.

Column (2) reports the results obtained from the estimation of (26) when the log of human capital index is included as an additional regressor. It might be argued that more sophisticated models require higher-skilled labour to be efficiently manufactured.⁴⁵ The aim of this estimation is then to assess whether the home market effect survives once we control for the relative availability of skilled labour. While the log of per capita GDP coefficient remains positive and statistically significant, the estimated value for the human capital index turns out to be not significantly different from zero. This evidence is suggestive of a predominant role of the home-market effect over relative skill abundance in determining quality specialisation.

Column (3) includes the log of physical capital stock per worker as additional regressor alongside $Y_{k,j}$. The intention here is to assess whether capital-abundant countries seem to enjoy a comparative advantage in higher-quality models. As it can be readily observed, the log of per capita GDP remains positive and statistically significant, after including this additional regressor. On the other hand, the coefficient associated to the stock of capital per worker is not significantly different from zero.

In column (4), we include as additional regressor a measure of financial development. The reason for looking into this regressor is that countries have different degrees of financial imperfections, which may heterogeneously influence the production costs of models of different quality levels. More generally, it may be the case that higher-quality varieties of fridges are relatively more dependent on availability of external finance (for example, if they require higher initial outlays of R&D investment). Similarly as in the previous two columns, the coefficient of log income per head remains positive. In this case, however, the financial development index carries an estimate that is positive and statistically significant. Our regression therefore consistent with the notion that access to financial markets plays an important role in influencing quality specialization.

All the previous results exploit variation in location choices regardless of the specific firm

⁴⁵For evidence linking labour 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 \(2018\)](#).

that produces each fridge model. In column (5), we reassess the impact of income per head on quality specialization but exploiting variation within brands only. In particular, we re-run the regressions including brand fixed effects.⁴⁶ 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. Comparing the estimates between columns (1) and (5), we can observe the coefficient associated with income slightly falls 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 correlation between income per head and quality remains positive and highly significant after including brand fixed effects. This finding suggests that the home-market effect is still present when we only exploit variation in location choices within firms. In other words, the home-market effect driving quality specialization across countries seems to be strong enough that it operates even when considering location choices within firms.

Column (6) reports the findings obtained by adding the brand fixed effects in the regression specifications used to produce the results in Column (4). Constraining the empirical analysis to within-brand variation does not modify our findings concerning the log of per capita GDP, whereas the log of financial development coefficient turns statistically insignificant. This result suggests that, while important across firms, the difficulties in obtaining local access to credit may be overcome within firms, possibly using financial resources obtained in a centralized fashion (e.g., in the country where the headquarters are located).

When combined with the evidence on nonhomothetic preference along the quality dimension presented in Section 4, the results in Table 7 point to the presence of a strong home-market effect as a key determinant of firms' production location choices. In particular, our results suggest that the strength of the home-market effect is so powerful that it operates not only across brands, but even within brands. That is, multi-plant brands tend to allocate the production of their higher-quality models in their plants located in richer countries. The finding that the home-market effect seems to dominate factor-endowment channels echoes the findings in [Dingel \(2017\)](#), albeit in a different context. Based on microdata on U.S. manufacturing plants across U.S. cities, [Dingel \(2017\)](#) shows that home-market effect tends to play a quantitatively more prominent role in explaining quality specialisation across U.S. cities than that linked to differences in relative factor

⁴⁶To keep the analysis brief, Table 7 only displays the results of regressions including brand fixed effects for the case when only income per capita, and income per capita and the financial development index are included as independent variables. The results of regressions analogous to columns (2)-(3) after including brand fixed effects follow similar qualitative patterns as that one in column (5) and are available from the authors upon request.

abundance. We show that similar results also arise when looking at quality specialization across different countries, and even within the same firms.

6 Conclusion

This paper inferred products' intrinsic quality from consumers choices by using a novel dataset following individual fridge models across different EU markets. The richness and granularity of the data allowed us to investigate a number of aspects associated with demand for quality and specialisation that have proven hard to tackle by previous efforts in the literature, which have typically relied on international transactions at the product level. These include testing and accounting for the presence of nonhomotheticities along the quality dimension, and its bearings on patterns of quality specialization at the firm level.

Our results cast strong support for demand for quality being nonhomothetic. By embedding a consumer choice model within a framework that allows for non-constant income elasticities, and that includes standard CES homothetic preferences as a special case, we have shown that market shares of higher-quality fridges are greater in markets with richer consumers. While this result echoes several related findings relying on unit values within product categories, our nonhomothetic results are based on comparing market shares of identical models across markets with different incomes. This allows us to cleanly elicit nonhomothetic demand schedules, without confounding the impact of varying willingness-to-pay for quality with changes in the composition of consumption bundles across different markets.

The presence of nonhomothetic preferences in a context of costly international transportation (as it is the case for bulky goods such as refrigerators), gives also prominence to the question of how local demand patterns impact on production location choices by firms. We show that location choices for fridges differing in their intrinsic quality are strongly affected by a home-market effect. Furthermore, a novelty of our dataset is that it allows us to exploit within firm variation in product location. Our results indicate that the impact of the home-market effect is so powerful that it drives quality specialisation, not only across firms, but also within firms. More specifically, brands with multiple plants choose to produce their higher-quality fridge models in their plants located in richer countries.

Finally, our results also highlight the importance of accounting for nonhomotheticities when assessing the impact of quality on demand at different levels of income. Quality measures inferred from preferences that are homothetic can sometimes differ quite substantively from those that are based on nonhomothetic ones. One main factor leading to such discrepancies in the context of the refrigerators seems to be how consumers' val-

uation for energy efficiency rises with their income. This carries an important message in terms of what aspects of technologies should firms aim at improving if they wish to increase penetration into richer markets. Furthermore, the finding of energy efficiency as one key feature to focus R&D efforts reaches far beyond the single case of the refrigerator industry. Almost all household appliances in the European Union must include an energy efficiency label. Therefore, provided consumers' valuation of energy efficiency behaves similarly across other household appliances, access to richer markets by firms in this industry can dramatically increase following improvements in their technologies that lead to more energy efficient products.

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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

$$\sum_{s \in \mathcal{S}} \sum_{j_s \in \mathcal{J}_{s,t}} p_{i,j_s,t} q_{i,j_s,t} \leq P_{i,t} Y_{i,t} \quad (\text{A.27})$$

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

$$\frac{\partial \mathcal{L}}{\partial q_{i,j_s,t}} = \frac{\alpha_s}{q_{i,j_s,t}} \frac{\lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}}{\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}}} C_{i,t} - \nu p_{i,j_s,t} = 0, \quad \forall t, j_s \in \mathcal{J}_{s,t}, s \in \mathcal{S}, i \in \mathcal{I} \quad (\text{A.28})$$

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.28) and rearranging, we obtain the country- i demand func-

tion of variety j_s in period t

$$q_{i,j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} C_{i,t}^{\sigma_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}} \right)^{-\sigma_s} p_{i,j_s,t}^{-\sigma_s} \lambda_{i,j_s} \quad (\text{A.29})$$

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

$$Q_{i,s,t} \equiv \sum_{j_s \in \mathcal{J}_{s,t}} q_{j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} C_{i,t}^{\sigma_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s}^{\frac{1}{\sigma_s}} q_{j_s,t}^{\frac{\sigma_s-1}{\sigma_s}} \right)^{-\sigma_s} \sum_{j_s \in \mathcal{J}_{s,t}} p_{j_s,t}^{-\sigma_s} \lambda_{i,j_s} \quad (\text{A.30})$$

imposing the identity $m_{i,j_s,t} \equiv q_{i,j_s,t}/Q_{i,s,t}$, using (A.29), (A.30), (2) and simplifying, we obtain (3).

A.1.1.2 Representative Household's Problem – Nonhomothetic case

Preliminarily, recall the utility function

$$\prod_{s \in \mathcal{S}} \left[\left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s-1}{\sigma_s}} \right)^{\frac{\alpha_s}{\sigma_s-1}} \right]^{\alpha_s} = 1, \quad (\text{A.31})$$

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

$$\sum_{s \in \mathcal{S}} \sum_{j_s \in \mathcal{J}_{s,t}} p_{i,j_s,t} q_{i,j_s,t} \equiv P_{i,t} Y_{i,t}, \quad (\text{A.32})$$

where $P_{i,t}$ is the price index associated to $Y_{i,t}$, and constrained by the preference representation as in (A.31). Letting ν denote the Lagrange multiplier on the constraint (A.31), 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

$$\frac{\partial \mathcal{L}}{\partial q_{i,j_s,t}} = p_{i,j_s,t} - \nu \frac{\alpha_s}{q_{i,j_s,t}} \frac{\lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}}}{\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}}} = 0, \quad (\text{A.33})$$

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.33) and rearranging, we obtain the country- i demand function of variety j_s in period t

$$q_{i,j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{-\sigma_s} p_{i,j_s,t}^{-\sigma_s} Y_{i,t}^{\varepsilon_{j_s}} \lambda_{i,j_s,t}. \quad (\text{A.34})$$

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

$$Q_{i,s,t} \equiv \sum_{j_s \in \mathcal{J}_{s,t}} q_{j_s,t} = \alpha_s^{\sigma_s} P_{i,t}^{\sigma_s} \left(\sum_{j_s \in \mathcal{J}_{s,t}} \lambda_{i,j_s,t}^{\frac{1}{\sigma_s}} Y_{i,t}^{\frac{\varepsilon_{j_s} - \sigma_s}{\sigma_s}} q_{i,j_s,t}^{\frac{\sigma_s - 1}{\sigma_s}} \right)^{-\sigma_s} \sum_{j_s \in \mathcal{J}_{s,t}} p_{i,j_s,t}^{-\sigma_s} Y_{i,t}^{\varepsilon_{j_s}} \lambda_{i,j_s,t}. \quad (\text{A.35})$$

Imposing the identity $m_{i,j_s,t} \equiv q_{i,j_s,t}/Q_{i,s,t}$, using (A.34), (A.35) and (2), simplifying and dropping the subscript s , we obtain (12).

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 (18) into account and facing the marginal cost $c_{k,j}$ and the transportation cost $\tau_{k,i}$; formally:

$$\Pi_{i,j}^k = \max_{p_{i,j}^k} (p_{i,j}^k - \tau_{k,i}c_{k,j}) \Omega_i \lambda_j (p_{i,j}^k)^{-\sigma} Y_i^{\bar{\kappa}(\lambda_j)}, \quad (\text{A.36})$$

which leads to the first order condition:

$$\frac{\partial \Pi_{i,j}^k}{\partial p_{i,j}^k} = 1 - \sigma (p_{i,j}^k - \tau_{k,i}c_{k,j}) (p_{i,j}^k)^{-1} = 0. \quad (\text{A.37})$$

We obtain (19) by simply isolating $p_{i,j}^k$ in (A.37). We may plug (19) into (A.36), which yields:

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

and, rearranging, leads to (20). The total profit (21) earned by the firm when model j is produced in country k results from the sum of (20), computed first with reference to $i = h$ and then to $i = l$. The profit ratio (22) is straightforwardly obtained by dividing (21) computed with reference to $k = h$ by the same expression computed with reference to $k = l$, and rearranging.

Proof of Lemma 1. Differentiating (22) with respect to λ_i yields:

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

where the inequality follows from noticing that $\Gamma'(\lambda_j) > 0$. □

Plugging the definition of marginal cost $c_{k,j} = \omega_k / \zeta_{k,j}$ into (22), we have:

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

which imposing the inequality $\varpi_j > 1$, after raising the whole expression to the power $1/(\sigma - 1)$ and rearranging, leads to (24). Plugging the definition of marginal cost $c_{k,j} = \omega_k / \zeta_{k,j}$ into (22), we have:

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

which imposing the inequality $\varpi_j > 1$, after raising the whole expression to the power

$1/(\sigma - 1)$ and rearranging, leads to (24). This condition implies that the probability that model j is produced in country h is $\Pr_j^h \equiv \Pr(\Pi_j^h > \Pi_j^l) = 1 - \Pr\left(\zeta_{h,j} \leq \zeta_{l,j} \Gamma(\lambda_j)^{-\frac{1}{\sigma-1}} \omega\right)$. Under a Frechet probability distribution, it follows that:

$$\Pr_j^h = \Pr_j^h = 1 - \frac{T_{l,j}}{\Lambda} \int_0^\infty \Lambda \zeta_{l,j}^{-2} \exp(-\Lambda \zeta_{l,j}^{-1}) d\zeta_{l,j} = 1 - \frac{T_{l,j}}{\Lambda}$$

where $\Lambda \equiv T_{h,j} \left[\Gamma(\lambda_j)^{-\frac{1}{\sigma-1}} \omega \right]^{-1} + T_{l,j}$. Rearranging and simplifying, rearranging, (25) immediately obtains.

Proof of Proposition 1. Preliminarily, note that $\Psi(\lambda_j) \equiv (T - \lambda_j + \psi A_h) / (T - \lambda_j + \psi A_l)$ has partial derivative with respect to λ_j :

$$\Psi'(\lambda_j) = \psi \frac{A_h - A_l}{(T - \lambda_j + \psi A_l)^2} \geq 0.$$

Furthermore, differentiating (25) with respect to λ_j , we may obtain:

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

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

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 (0.014)***	-0.047 (0.016)***
$L^{-3} \ln(ER) \times \text{High Income}$	-0.032 (0.019)	
$L^{-3} \ln(ER) \times \text{High Efficiency}$		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 $\ln(\text{Price})$. 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 21 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)	$\hat{\theta}_j^h$	$\hat{\theta}_j^{nh}$
	(1)	(2)	(3)
A+++	0.145 (0.063)**	0.599 (0.139)***	2.626 (0.244)***
A++	0.017 (0.066)	0.312 (0.118)**	2.193 (0.184)***
A+	-0.045 (0.046)	0.153 (0.103)	1.383 (0.157)***
A	-0.048 (0.040)	0.067 (0.091)	0.419 (0.121)***
Zero-degree box	0.214 (0.094)**	0.342 (0.144)**	0.149 (0.046)***
Freezer side	0.549 (0.052)***	0.812 (0.061)***	0.248 (0.075)***
Dispenser	0.120 (0.063)*	0.246 (0.078)***	0.080 (0.056)
No-frost system	0.224 (0.049)***	0.277 (0.098)***	0.465 (0.059)***
ln(Noise Level)	-0.454 (0.338)	-1.449 (0.612)**	-1.656 (0.640)**
Display	0.202 (0.026)***	0.221 (0.026)***	-0.031 (0.059)
Metal exterior	0.054 (0.015)***	0.101 (0.038)**	0.061 (0.045)
N ^o doors	0.198 (0.041)***	0.396 (0.048)***	0.198 (0.067)***
Brand	Yes	Yes	Yes
N	2,069	2,069	2,069
R ²	0.774	0.663	0.635

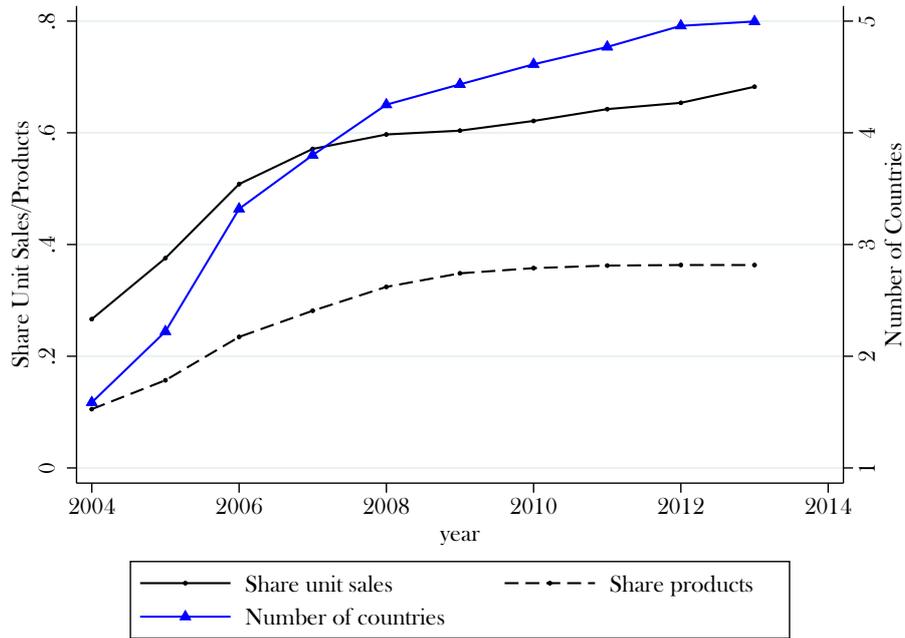
Notes: This table repeats Columns (2) and (6) from Table 5 and compares these results to a measure of quality derived under the assumption of nonhomothetic preferences. The dependent variable is the log of Price in Column (1), inferred quality based on eq. (8) under homothetic-preferences assumption in Column (2), and inferred quality based on eq. (17) 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 – QUALITY AND PRODUCTION LOCATION

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			$\widehat{\theta}_j^h$			
log(GDP p.c.)	0.751 (0.215)***	0.723 (0.218)***	0.877 (0.394)**	0.706 (0.211)***	0.547 (0.274)*	0.534 (0.273)*
Human Capital Index		0.024 (0.239)				
log(Physical Capital Stock p.c.)			-0.096 (0.209)			
log(Financial Development Index)				0.086 (0.037)**		0.038 (0.032)
Brand	No	No	No	No	Yes	Yes
R ²	2,069	1,983	2,069	2,068	2,068	2,067
N	0.155	0.145	0.156	0.165	0.420	0.422

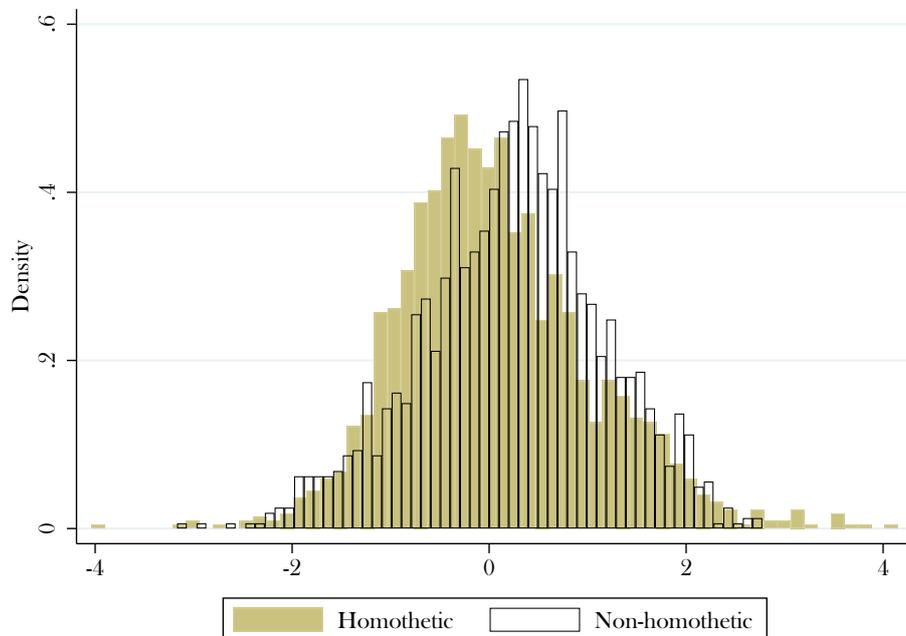
Notes: The dependent variable is the estimate of inferred quality obtained from eq (8) under the assumption of homothetic preferences. Log per capita GDP, human capital index and log per capita physical capital stock are retrieved from the Penn World Tables. Log financial development is retrieved from World Bank Database, using private credit over GDP. Standard errors in parentheses are robust in all specifications and clustered by brand. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE A.1 – REFRIGERATORS: TRENDS IN MULTI-COUNTRY TRADE



Note: 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 – INFERRED QUALITY ESTIMATES DISTRIBUTION



Note: 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. (8). The data is then collapsed at the product level.

A.2 Identifying country of origin

The data collection of refrigerator models' country of origin was mainly conducted using three separate sources of data, namely through: a) Examination of a product's "Declaration of Conformity" and "Certificate of Conformity", issued under the Authority of the Custom Union of Republic of Belarus, the Republic of Kazakhstan and the Russian Federation (EEU) in order to fulfil the agreement on common principles and rules of technical regulation that the State Members signed on November 18, 2010; b) Inspection of a product's instruction manual; c) Investigation of web scraped data from major Russian online retailers.

We provide more details on each source below. Each product was linked to the information so obtained through its Model Reference Number (MRN) issued by the relevant producer. The information was extensively corroborated by cross-referencing the above-listed sources. We have found no evidence of appliances being manufactured in more than one production location throughout their market life.

1. Declarations/Certificates of Conformity Manufactured goods' Declaration of Conformity and Certificate of Conformity were introduced by the EEU to certify that the approved products fulfil essential requirements, analogous to those required by the EU. Unlike the EU Certificate of Conformity, however, the CU also requires the applicant to include, among a number of other distinctive items, information on the location where the product is manufactured. A number of Internet sources were used to access to the relevant Declarations and Certificates, including: Eurasian Commission website (<http://www.eurasiancommission.org>); Eurasian Economic Community website (<http://www.evrazes.com>); East Certificate website (<http://www.east-certificate.eu>); Custom Union Certification and Declaration website (<http://customsunioncertificate.com>)).
2. Instruction manuals Instruction manuals were individually inspected to assess whether they contained information on a model's production location. In some cases, the instruction manuals refer to groups of refrigerators with distinct MRNs: under these circumstances, the information was used for every refrigerator belonging to the relevant group. A number of Internet sources were used to access to the relevant instruction manuals, including: Rembitteh website(www.rembitteh.ru); McGrp website (www.mcgrp.ru); Mnogodok website (www.mnogo-dok.ru); Manuals Directory website (www.manualsdir.ru); ManualsPDF website (www.manualspdf.ru).
3. Web scraping The web scraping activity was directed towards specific websites, which we individually identified by browsing online shops, stores, retail chains and

marketplaces in virtually every country appearing in our main database. Data extraction from websites was automatized using tools such as the Google Chrome Web Scraper plugin and the webscraper.io tool (<https://www.webscraper.io>). The collected information was then manually checked for consistency. A number of Internet sources were used to access to the relevant instruction manuals, including: www.goods.ru – online platform and marketplace created by ‘m.video’; www.dns-shop.ru – Internet shop and retail chain specializing in the sale of electronic devices and home appliances in the Russian Federation; www.eldorado.ru – trading network selling household appliances and electronics; the company is part of the m.video-Eldorado Group, the largest retail company in the Russian Federation; www.holodilnik.ru – online store specializing in the sale of all types of household appliances of domestic and foreign production; www.citilink.ru – Russian chain of stores selling computer, digital and household appliances.

4. Further investigation Some of the brands included in our database have only one manufacturing location. This information, which was gathered directly from the official website of each brand involved, was automatically linked to every model produced by the relevant brand. Online catalogues and consumer websites were also surveyed to extend the coverage of our country of origin database. Some of these sources indeed included general overview of the products, which sometimes also featured their countries of origin. The sources used in this type of investigation include: www.btest.ru; www.holodilnik.info; www.holodilnik-info.ru; www.xolodilnik.info; www.potrebitel.info; www.vashdom.info.

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