Do the rich (really) consume higher quality goods?

Evidence from international trade data*

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Abstract

We provide novel evidence on the relationship between importer income and quality of im-

ports, building on Khandelwal's (2010) discrete choice approach. The disaggregated product quality measure delivered by our model is inferred by quantitative market shares as well as import prices; and features an additional component, which explicitly relates to consumer income. In testing the relationship between income and quality, we exploit the new component of our quality measure. Hence, our approach does not rely on prices as direct proxies for quality, an option often criticized since prices could be affected by other factors than product quality. We validate the model's prediction using the Eurostat's COMEXT database, which collects disaggregated customs data reported by EU countries. Our findings

indicate the existence of a positive link between income and quality, and are robust to a

number of different specifications and controls. Based on our estimates, we also develop a

novel quality upgrading indicator that conveniently quantifies import quality improvements

as importer income rises.

Keywords: import quality, import shares, unit values, nested logit demand

JEL Classifications: F12, F14, L15

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1 Introduction

This paper provides novel evidence on the relationship between importer income and quality of imports. We extend Khandelwal's (2010) approach that infers product quality measure from data on prices and market shares by developing a parsimonious discrete choice model in which richer consumers demand goods of higher quality. The resulting quality measure features an additional component, which relates to consumer income. By focusing on this novel component rather than import prices (or unit values), we are therefore able to test the link between quality and income departing from the traditional assumption that information on quality is fully embedded in prices.

The relationship between product quality and consumer income is found to be an important determinant of import and export flows in a number of theoretical contributions: e.g., Flam and Helpman (1987); Murphy and Shleifer (1997); and, more recently, Fajgelbaum, Grossman and Helpman (2011); Benedetti Fasil and Borota (2013); Jaimovich and Merella (2012, 2015). In all these articles, the main prediction is invariably the following: richer importers tend to trade more with exporters producing higher quality goods. The link between importer income and quality of imports also appears to find support in the empirical literature: e.g., Hummels and Klenow (2005); Hallak (2006); Bastos and Silva (2010); Fieler (2011); Flach (2014). The extent to which such empirical findings actually relate to the theoretical prediction is, however, controversial. The crux of the matter is that unit values are typically used as proxies for the quality levels of the imported goods.

Unit values are calculated at the product level as the ratio between the total value and the total volume traded from a source country (exporter) to a destination country (importer). The rationale for using them as proxies for quality hinges on a number of arguments: e.g., higher quality goods would require more costly inputs, hence be more expensive; a market price differential between two similar goods may hold only if their quality levels differ. Several authors, however, argue that the correlation between prices and income may actually be determined by factors other than quality: e.g., Hallak and Schott (2011); Simonovska (2010). The most immediate argument is that goods sourced from different countries may command heterogeneous tariffs and

¹Further, within country, evidence that richer consumers typically purchase product of higher quality can be found, for example, in Bils and Klenow (2001), Broda and Romalis (2009), and Choi, Hummels and Xiang (2009).

trade costs. Furthermore, exporters may charge varied markups in different markets (pricing-to-market), which could lead to systematically higher prices imposed in more developed economies.² Finally, even products that are regarded as close substitute may exhibit some distinctive characteristics, which could result in a certain residual degree of horizontal differentiation.

Building on this criticism, part of the literature attempts to construct alternative quality measures that do not rely solely on prices. For example, Khandelwal (2010) and Pula and Santabárbara (2012) use quantitative market shares to obtain a quality measure for the goods exported by a given country; Hallak and Schott (2011) bring in trade balances. The idea behind these two approaches is to extract information on quality from trade volumes holding prices constant, building on the intuition that consumers care about price relative to quality in choosing among products. Hence, two goods with the same price but different trade volumes should have different levels of quality.³

This paper follows (by gathering information on quality from volumes of trade and import prices) and extends (by letting willingness to pay for quality rise with income) the first of these two approaches.⁴ We use a nested logit demand system to infer information on quality from quantitative market shares as well as import prices. Consumers face a set of vertically and horizontally differentiated goods, produced by monopolistically competitive firms. They have objective taste for quality, whose different levels are identified on the vertical dimension, and idiosyncratic tastes for the specific characteristics that horizontally differentiate products with the same level of quality. To this standard representation, we add a preference feature that allows for willingness to pay for quality to rise with income. Therefore, our framework allows for the valuation of quality to be income-dependent.⁵

From a theoretical standpoint, our prediction is in line with those found in the literature:

² Alessandria and Kaboski (2011) provide further evidence of this phenomenon, showing that US exporters ship the same goods to low-income countries at lower prices.

³Another important contribution to disentangling quality and unit values is due to Feenstra and Romalis (2014). These authors add a richer supply side specification to the demand side intuition upon which the two approches discussed in the text are developed.

⁴We choose to follow more closely the first approach because the richness of observations in our dataset allows for a more refined analysis than that based on world-level exports. We are aware that a "disadvantage is that [...] one-way flows to a single country are likely to be substantially more sensitive to mismeasurement of trade costs than countries trade balances with the world." (Hallak and Schott, 2011; footnote 21, p.434.) For this reason, we implement a number of controls in our empirical work, which we discuss in Section 3.

⁵Feenstra and Romalis (2014) also feature a nonhomothetic specification of demand: its parameterization, however, relies on unit values (specifically, free on board import prices).

richer importers purchase their goods from exporters producing higher quality products. The novel feature in our approach is how this theoretical prediction is validated empirically. Instead of studying the link between importer income and average import price, we investigate how importer income influences a quality measure, derived within the model, that takes into account products' quantitative market shares as well as prices.

In conducting our empirical analysis, we exploit the unique features of Eurostat's COMEXT database, which provides information on each EU member state's imports from 240 partner economies at the CN-8 digit product level (approximately 8500 product headings). This information is used to obtain a highly disaggregated measure of the product quality levels (for each 8-digit product and every exporter) imported by each EU country. The underlying strategy is to consider different members of the EU as consumers operating in a single market. We can then test the relationship between quality and income using countries GDP per capita as a proxy for the latter. Our findings suggest a robust positive correlation between income and product quality. Specifically, as we illustrate in Section 3, our results are robust to different specifications, do not rely on any particular sector, and are also robust to a number of controls and alternative instrumentation strategies.

An important corollary of our analysis is that our estimates allow us to develop a novel quality upgrading indicator, which provides a key practical figure to quantify import quality improvements as importer income rises. As we discuss in greater details in Section 3.3, this indicator represents a promising tool for illustrating and analyzing the quality dimension of demand structure, even at the sectoral level. According to the indicator, for example, we can infer that import quality rises on average by about 2.75% relative to the length of its quality ladder (*i.e.*, the space of available qualities) in response to a ten percent increase in importer income.

Our paper relates to contributions building on the tradition of models with a nested logit demand structure, first proposed by McFadden (1973), and later developed by Berry (1994) and Berry, Levinsohn, and Pakes (1995). This modeling strategy has been applied to international trade by Goldberg (1995) and Verboven (1996) and, more recently, by Verhoogen (2008) and Khandelwal (2010). Here, we extend these works by introducing a mechanism that leads to a link between product quality and consumer income. It should be noted that Fajgelbaum,

Grossman and Helpman (2011) also introduce willingness to pay for quality in a model with a nested logit demand system. Their study, however, is exclusively theoretical, and aims to explain why richer countries *export* higher-quality goods, whereas our quantitative model is designed to empirically test the link between product quality and *importer* income.⁶

The remaining of the paper is organized as follows. Section 2 illustrates the model from which we derive our predictions. Section 3 describes our empirical strategy, shows that our estimations support the theoretical predictions of the model, and offers a discussion about the meaning and the implications of our findings. Finally, section 4 concludes.

2 Theoretical framework

This section builds on the tradition of the nested logit discrete choice models.⁷ Most features of our model are standard: (i) we consider a partial equilibrium world economy where a large number of independent markets exist; (ii) throughout the whole theoretical analysis, we restrict our attention to a single, representative, market;⁸ (iii) products are potentially sourced from, and destined to, several countries: to simplify matters, we only consider two source countries, denoted N and S, and two destination countries, denoted H and L. The novel feature of our approach is that (iv) we allow for willingness to pay for quality to rise with income. Adding this last feature allows us to obtain a direct link between consumer income and the product quality measure delivered by the model; link that we investigate empirically in Section 3.

Within every source country there is a unit mass of firms, indexed by j, each producing a differentiated good. Labor inputs are immobile (which allows for different wages in N and S) and technologies differ across countries. We assume that country N enjoys higher wages $(w_N > w_S)$ and technological capabilities $(A_N > A_S)$ than country S. Every destination country is populated by a continuum of consumers. The two countries differ in their income levels and (possibly) size, and we assume that country H is richer $(y_H > y_L)$ than country L. Size is denoted by ψ and

⁶ In fact, the divergence in the goal of the two papers entails a fundamental difference in the modeling strategy. Fajgelbaum *et al.* (2011) develop a general equilibrium model where idiosyncratic tastes have a generalized extreme value (GEV) distribution, whereas we opt for a partial equilibrium model with idiosyncratic tastes having a type I extreme value distribution.

⁷For a textbook description of this model, see Tirole (1988).

⁸The arguments discussed here naturally extend to all sectors considered in our empirical investigation, which we then present in Section 3.

expressed in relative terms, hence the destination region has size one, and $\psi_L \equiv 1 - \psi_H$. Two additional features complete the model. First, outside sectors determine wages and incomes. Second, domestically produced outside varieties are available to consumers in every sector of each destination country.

By differentiating their products, firms in the source region engage in monopolistic competition. They exercise their degree of market power by setting the prices of their products taking consumer demand into account. For this reason, we begin our analysis by studying consumer choice. Each individual i in country $M = \{H, L\}$ may consume one unit of a differentiated good (j, X), produced by firm j in country $X = \{M, N, S\}$. Good (j, X) is shipped to M in the quality level $q_{j,X}^M$ (which is agreed upon by all consumers) and with specific horizontal traits (whose valuation is instead consumer-specific).

Valuation of good (j, X) by consumer i in country M is represented by the indirect utility function:

$$V_{j,X}^{i,M} = \theta^M q_{j,X}^M - \alpha p_{j,X}^M + \varepsilon_{j,X}^{i,M} \tag{1}$$

where θ^M reflects the country-M consumers' (common) valuation for quality, $p_{j,X}^M$ is the price of good (j,X) when traded in country M, α represents consumers' (worldwide common) price sensitivity and $\varepsilon_{j,X}^{i,M}$ is the valuation for the horizontal differentiation term. We introduce the concept of rising willingness to pay for quality as income increases by assuming that valuation for quality is an increasing function of income.

Assumption Valuation for quality $\theta^{M} \equiv \theta\left(y_{M}\right)$ is such that $\theta\left(0\right) > 0$ and $\partial\theta\left(y_{M}\right)/\partial y_{M} > 0$.

As a result, the larger y_M , the higher θ^M , and the greater the willingness to pay for quality, all other conditions holding constant.

Under the assumption that the horizontal valuation term $\varepsilon_{j,x}^i$ follows a Gumbel distribution, the expected aggregate demand for good (j,X) by country M is:

$$c_{j,X}^{M} = \frac{\psi_{M} \exp\left(\delta_{j,X}^{M}\right)}{\sum_{Y=\{M,N,S\}} \int_{0}^{1} \exp\left(\delta_{k,Y}^{M}\right) dk}$$

$$(2)$$

where $\delta_{j,X}^M \equiv \theta^M q_{j,X}^M - \alpha p_{j,X}^M$ represents the average valuation of good (j,X), which is independent

dent of $\left\{ \varepsilon_{j,X}^{i,M} \right\}$ since idiosyncratic elements vanish when aggregating across consumers.

In each country of the source region, firms compete by producing vertically and horizontally differentiated goods. Vertical differentiation consists of choosing a particular quality version of the supplied good. To produce one unit of quality q, a firm in country X faces the cost $w_X + q^2/(2A_X)$. (Recall that A_X is a country-specific technological parameter, and wages w_X are determined by an outside sector and, as such, are exogenous.) Horizontal differentiation consists of choosing whether to embed specific characteristics to further individualize the supplied good. All firms horizontally differentiate goods at no additional cost.

Each firm j in country X take country-M consumer demand (2) into account when choosing price $p_{j,X}^{M}$ and quality $q_{j,X}^{M}$ to maximize profits:

$$\pi_{j,X}^{M} = \max_{p,q} \left(p - w_X - \frac{q^2}{2A_X} \right) \frac{\psi_M \exp\left(\theta^M q - \alpha p\right)}{\sum_{Y = \{M,N,S\}} \int_0^1 \exp\left(\delta_{k,Y}^M\right) dk}$$
(3)

(Atomless) firms cannot influence the equilibrium allocations, so the optimal price charged is:

$$p_{j,X}^{M} = \frac{1}{\alpha} + w_X + \frac{\left(q_{j,X}^{M}\right)^2}{2A_X} \tag{4}$$

and the optimal quality is:

$$q_{j,X}^{M} = \frac{\theta^{M} A_{X}}{\alpha} \tag{5}$$

From (4) and (5), we may note that: (i) all firms within each source country optimally supply to country M goods of the same quality level $(q_{j,X}^M = q_X^M, \forall j)$, which are hence equally priced $(p_{j,X}^M = p_X^M, \forall j)$; (ii) since $A_N > A_S$, goods produced in N are always of higher quality than those produced in S; (iii) by replacing (5) into (4) it turns out that $p_X^M = w_X + \left(\theta^M\right)^2 A_X / \left(2\alpha^2\right) + 1/\alpha$ and, since $w_N > w_S$, goods produced in N are also more expensive than those produced in S.¹⁰

Recall that valuation for quality is an increasing function of consumer income. Considered in conjunction with (5), this feature of the model delivers the central prediction of our paper, which we may summarize as follows.

⁹We illustrate the formal derivation of aggregate demand (2) in Appendix A.1.

¹⁰We illustrate the formal derivation of optimality conditions (4)-(5) in Appendix A.2.

Proposition. Goods sourced from country X to the destination country H are always of higher quality than those sourced to L:

$$q_X^H > q_X^L, \ \forall X$$

Proof. The result immediately follows from noticing that, since $y_H > y_L$, then $\theta^H > \theta^L$ from Assumption 1, hence $q_X^H = \theta^H A_X/\alpha > \theta^L A_X/\alpha = q_X^L$ from (5).

This result implies that richer consumers (higher y), displaying higher willingness to pay for quality (larger θ), have a different demand structure than poorer consumers and, in particular, tend to import higher quality goods. The central prediction of our model is therefore in line with those found in the literature: product quality and importer income should be positively related.

The novel feature in our approach is how this theoretical result translates into an empirical test. As we discussed in the previous section, empirical contributions investigating the correlation between importer's income and consumption goods' quality typically use unit values (average import prices) as proxies for quality. We depart from the literature and infer product quality from (quantitative) market shares in a direct fashion, once unit values are controlled for.

In order to offer a more accurate description of the link between theoretical prediction and empirical test, it proves convenient to derive how import volumes translate into quantitative market shares, relative to the domestic market share. To do so, first notice that we may obtain total consumption c^M in the destination country M by summing up aggregate demand (2) across source countries:

$$c^{M} \equiv \sum_{X = \{M, N, S\}} \psi_{M} \frac{\exp\left(\delta_{X}^{M}\right)}{\sum_{Y = \{M, N, S\}} \exp\left(\delta_{Y}^{M}\right)} = \psi_{M}$$

We then derive the market share of the source country X in the destination country M by computing the ratio between the relevant aggregate demand and total consumption:

$$s_X^M \equiv \frac{c_X^M}{c^M} = \frac{\psi_M \exp\left(\delta_X^M\right)}{\sum_{Y=\{M,N,S\}} \exp\left(\delta_Y^M\right)} \frac{1}{\psi_M} = \frac{\exp\left(\delta_X^M\right)}{\sum_{Y=\{M,N,S\}} \exp\left(\delta_Y^M\right)}$$
(6)

Following the literature, we can further simplify this expression by normalizing to zero the average valuation of the domestically produced goods (j, M), which amounts to imposing $\delta_M^M =$

 $\theta^M q_M^M - \alpha p_M^M = 0$. Using (6), the domestically produced goods market share is:

$$s_M^M = \frac{\exp\left(\delta_M^M\right)}{\sum_{Y=\{M,N,S\}} \exp\left(\delta_Y^M\right)} = \frac{1}{\sum_{Y=\{M,N,S\}} \exp\left(\delta_Y^M\right)}$$
(7)

As a result, the relative quantitative market share of the source country X in the destination country M is given by the ratio of (6) to (7):

$$\frac{s_X^M}{s_M^M} = \frac{\exp\left(\delta_X^M\right)}{\sum_{Y=\{M,N,S\}} \exp\left(\delta_Y^M\right)} \left(\frac{1}{\sum_{Y=\{M,N,S\}} \exp\left(\delta_Y^M\right)}\right)^{-1} = \exp\left(\delta_X^M\right) \tag{8}$$

Taking logarithms, and using the definition of average valuation for good (j, X) in the destination country M to replace δ_X^M , we obtain the equation that we bring to the data in order to infer our measure of product quality and its relationship with importer income:

$$\ln s_X^M - \ln s_M^M = \delta_X^M = \chi_X^M - \alpha p_X^M \tag{9}$$

where $\chi_X^M \equiv \theta^M q_X^M$ is the observationally relevant variable.¹¹

This result, implied by the logistic nature of the model, represents the cornerstone of this type of models. From an empirical point of view, since quantitative market shares and prices are observable whereas qualities are not, the latter may be inferred by market shares once the effect of price is accounted for. That is, not only for a given quality the ability to obtain a larger market share is stronger if the product is available at a lower price since, for $\chi_X^M = \ln s_X^M - \ln s_M^M + \alpha p_X^M$ to hold constant, s_X^M and p_X^M must be negatively related. But most importantly, for a given p_X^M (and s_M^M) quality is deduced to be higher if the product captures a larger market share, since by (9) s_X^M and χ_X^M must be positively related.

The novelty of our analysis lies in investigating the relationship between consumer income and product quality within this framework, where the newly developed quality measures replace average import prices as proxies for quality. In this context, with rising income, even if the

¹¹This definition is due to the impossibility to identify θ^M and q_X^M separately. This caveat does not represent a major issue, since: (i) θ^M is the same for all goods imported by a given country, hence it works as a mere scale factor applied to a measure (quality) that is ordinal by nature; (ii) when comparing goods imported by different regions, this scale factor only magnifies the difference between (ordinal) quality levels: the mapping between $\{q_X^M\}$ and $\{\theta^M q_X^M\}$ is monotonic since q_X^M is an increasing function of θ^M .

relative market share remained constant, the higher capability and willingness to pay for quality would entail a simultaneous rise in both quality and price of the importer good. Formally, if $\ln s_X^M - \ln s_M^M$ held constant, then an increase in χ_X^M (in turn due to a growing θ^M with y_M) would require a proportional rise in p_X^M to keep the right-hand side of (9) fixed. In fact, quality of imports might rise even if the relative market share declined, provided that a sufficiently large increase in price would also be observed. Specifically, if the rise in the term αp_X^M were larger than the decrease in the term $\ln s_X^M - \ln s_M^M$, then χ_X^M would have to grow for the equality in (9) to hold.

3 Empirical approach

As we have shown in the previous section, our model predicts that the quality embodied in each traded good is an increasing function of importer income. This prediction can be empirically tested using (9). Since market shares and prices are observable, quality may be inferred by (quantitative) market shares once the price effect is taken into account. In what follows, we first illustrate the data that we use to test our prediction, and describe how we develop our estimations. We then present our empirical results. Finally, we interpret these results by reviewing a number of their features, which lead us to develop a novel indicator of the response of product quality to variations in importer income.

3.1 Dataset and estimation strategy

We estimate the demand function (9) for each sector using data from the Eurostat's COMEXT database. The COMEXT database collects EU harmonized customs data and contains information on all trade flows reported by each EU country. It is a disaggregated data source, which provides trade data at the CN8-digit product level.¹² In particular, this database contains values and quantities of all imports for each EU country. For a more homogeneous data availability and to obtain a properly balanced panel, in our empirical exercise we consider five developed

¹²For example, we are able to distinguish within the men's knitted shirt category (CN 4 digit code 6105) by material: cotton (61051000), synthetic fibre (61052010), artificial fibre (61052090), wool (61059010), or other material (61059090).

Table 1. Summary statistics.

	Sector (NACE-2)	No. of 4-digit sectors	No. of products	No. of varieties	No. of importers (M)	No. of exporters	No. of observ. (<i>M</i> , <i>z</i> , <i>t</i>)	No. of products per eq.	No. of varieties per eq.	No. of observ. per eq.
15	Food	18	715	29,479	5	243	324,634	96	3,909	44,266
16	Tobacco	1	9	463	5	131	4,690	9	463	4,690
17	Textile	5	119	40,469	5	229	116,397	32	2,097	31,477
18	Wearing apparel	5	309	30,318	5	244	493,637	100	9,712	167,569
19	Leather and shoes	2	87	13,490	5	229	93,673	42	3,436	47,615
22	Publishing	1	4	3,696	5	123	3,647	4	316	3,647
24	Chemicals	3	153	22,856	5	212	105,746	57	2,508	35,987
35	Other transport	2	33	8,650	5	195	33,547	18	1,226	17,707
36	Furniture and other	3	44	16,316	5	216	53,841	25	1,681	28,964
	Total	40	1,473	165,737	5	202	1,229,812	42	2,816	42,436

Note. The table reports several descriptive statistics of the sample, for each 2-digit sector. A variety is defined as a product (according to the 8-digit classification) imported from a given country. All sectoral references are based on the NACE classification. **Source.** Authors' calculations based on the dataset described in Section 3.1.

countries among the EU members, namely: Germany, France, Italy, Spain and the UK.¹³ Accordingly, our database is four dimensional: it contains import data for 5 destination EU countries (M) under 8500 product labels (g) from 240 trade partners (X) for the 1995-2007 period (t). In what follows, we denote the good imported under product label g from country X as a variety z = (g, X). As such, in our analysis a variety can be seen as the basic unit of importer choice.¹⁴

In our analysis, all varieties belonging to undifferentiated products are dropped, as building a quality index based on such varieties would make little sense; furthermore, since our theory concerns consumers, we keep only varieties belonging to consumer-good intensive categories. The varieties are selected using Rauch's (1999) differentiated products classification on the one hand, and the Eurostat's Main Industrial Groupings on the other.¹⁵ Table 1 gives an overview of the database at a 2-digit level. Overall, the database contains 40 four-digit sectors. On average,

¹³These five countries are the largest markets within EU, which guaratees that they import a comparable set of products from their trade partners. Besides, the selected countries are among the richest in the world (the relevant per capita GDP figures are well above 30,000 international dollars; source: World Bank, 2013), and display fairly similar income distributions (e.g., the relevant Gini coefficients range from 0.28 to 0.35; source: Eurostat, 2012).

 $^{^{14}}$ Note that horizontal differentiation, as discussed in the previous section, occurs at the product level. As a result, every variety z includes each differentiated goods j, belonging to label g, produced in source country X.

¹⁵Since considering only consumer-good intensive varieties significantly reduces the size of the database, for robustness we also perform our empirical analysis using all differentiated varieties, regardless their end-use categorization. The results hold qualitatively intact. We report the relevant findings in the Online Appendix, available at http://sites.google.com/site/vincenzomerella/research/files/OnlineAppendixDRCHQG.pdf.

per equation, we have 42 products g, nearly three thousands varieties z and more than forty thousands observations (z,t). The coverage of the database varies significantly across the 2-digit sectors. For example, the wearing apparel sector has on average almost ten thousands varieties per equation, while the publishing sector has just over three hundreds.¹⁶

In order to guarantee a certain homogeneity in the demand function for the differentiated products, we estimate a separate demand function for each NACE 4-digit sector.¹⁷ Due to data availability, the number of separate equations we can actually estimate reduces from 40 to 39. Taking all the specifics of our database into consideration, we can rewrite (9) as:

$$\ln s_{z,t} - \ln s_{0,t} = \chi_z + \chi_t + \chi_M + \chi_y - \alpha p_{z,t} + \sigma \ln n s_{z,t} + \chi_{z,t}$$
(10)

This is the equation that we estimate separately for each NACE 4-digit sector. In each destination country, $s_{z,t}$ measures the market share of variety z relative to total consumption of goods in the relevant 4-digit sector, in turn computed as the sum of domestic production and imports, minus exports. The market share is calculated in quantitative terms. We also consider an outside variety, required by the demand system, as the domestic substitute for imports in each country, whose market share, $s_{0,t}$, is calculated as one minus the sectoral overall import penetration.¹⁸

In equation (10), we estimate quality —the term χ_X^M in (9)— as the sum of five components: (i) the time invariant component (χ_z) , captured by variety fixed effect; (ii) the common trend component (χ_t) , captured by year fixed effect; (iii) the destination market component, captured by importer dummy (χ_M) ; (iv) an unobserved component $(\chi_{z,t})$, captured by the estimation error term; and (v) the income effect component, $\chi_y \equiv \beta \ln y_M$, obtained by introducing the log of importer per-capita GDP as a regressor in (10). The β parameter is the central object of interest of our analysis. In equation (10), this parameter governs how a market share relate to product quality. Since our model predicts that product quality increases with importer income, we expect $\beta > 0$.

¹⁶While our estimates are based on a large but not particularly balanced panel of data, this fact does not represent an issue since, as we discuss below, each sector is by construction independently considered.

¹⁷Each 4-digit NACE sector is linked to the relevant CN 8-digit classification through appropriate correspondence tables provided by EUROSTAT.

¹⁸The sectors are identified by the NACE 4-digit classification because this is the most disaggregated level at which import penetration data are available for calculating domestic market shares in consumption.

The demand function (10) allows for different degrees of substitutability across products. In fact, in a nested logit specification of demand, different substitutability patterns may arise among groups of varieties or 'nests', which must however be determined ex-ante. We let product labels g serve as nests. In particular, it is assumed that varieties within the same product exhibit a higher degree of substitutability than varieties of different products. For example, a Vietnamese cotton shirt is assumed to be a closer substitute to a Chinese cotton shirt than a Chinese nylon shirt. ¹⁹ The nest term $ns_{z,t}$ is calculated as the import share of variety z in the total imports of product g (the nest), and is introduced to limit the extent of the issues arising from the independence of irrelevant alternatives in traditional logit models. ²⁰

The substitution parameter σ can be interpreted as follows. If σ approached one, there would be perfect substitution among varieties within the nest (e.g., between Chinese and Vietnamese cotton shirts), but no substitution across nests (e.g., no substitution between cotton and nylon shirts). As a result, if the price of a given variety increased, importers would substitute it with varieties from the same nest but not from other nests. On the one hand, this would imply that the varieties' relative market share would change within the nest, but not outside the nest, and thus changes in the overall market share $s_{z,t}$ would be exclusively determined by the share $ns_{z,t}$ within the nest.²¹ In fact, in the case of an increase in its relative price, a variety easier to substitute would have a stronger decline in its market share, even if no change occurred in its relative quality. On the other hand, market shares of varieties in a given nest would not be influenced by price variations occurring to varieties in other nests. Of course, if σ approached zero, then the opposite would occur.

Given that the price $p_{z,t}$ and the nest share $ns_{z,t}$ are endogenous, *i.e.*, contemporaneously correlated with the residual $\chi_{z,t}$, in order to obtain consistent estimates of (10) we consider a number of instruments. For the unit values, $p_{z,t}$, we use two sets of instruments. Given that

 $^{^{19} \}mathrm{In}$ this example, cotton shirts and nylon shirts are two distinct nests.

 $^{^{20}}$ Theoretically, $ns_{z,t}$ should be calculated as a market share in consumption. However, given that we have no information on the size of the domestic market at the product level, we calculate it as an import share, *i.e.*, as the share of variety z import in the total imports of product g. This is equivalent to the assumption that each product market in a given sector exhibits the same import penetration.

²¹In the example introduced above, if the price of the Chinese cotton shirt went up, importers would substitute it with Vietnamese cotton shirts and not by Chinese nylon shirts. The overall market share of both cotton and nylon shirts would remain unchanged, while the market share of Chinese cotton shirt within the apparel sector would fall together with its share within the cotton shirt nest.

the COMEXT database contains neither variety-level transportation costs nor non-rival variety characteristics (which are widely used instruments in the literature since Hausman, 1997), our first set of instruments relies on non-variety specific data, and in particular on country level data, namely the bilateral exchange rate and a proxy for transportation costs calculated as the interaction of bilateral country distances and the oil price.²² This set of instruments has the advantage of being available for the whole sample. The second set of instruments is variety-specific, and consists of the average unit values of each variety observed on alternative EU markets. The idea behind using these so called Hausman instruments is that changes in unit values in third markets can be assumed to reflect cost shocks and thus be used as instruments for prices with regard to the EU member state market under consideration.²³ The nest share, $ns_{z,t}$, is instrumented with the number of varieties within the nest and with the number of varieties exported by the source country.

In what follows, we compare the results obtained using three methods: the ordinary least square estimation (labelled 'OLS'), which does not deal with endogeneity issues; and two instrumental variable estimations, one making use of the subset of non-variety-specific instruments only ('IV1'); and the other using the full set of variety and non-variety specific instruments ('IV2').

3.2 Estimation results

To give an overview of the goodness of the regressions, Table 2 reports a summary of the estimation results, focusing on the coefficient of our variable of interest, *i.e.*, the log of per capita GDP (hereafter, GDP coefficient).²⁴ Given the relatively large number of separate equations, one per 4-digit sector, the table shows the distribution of the coefficients and of the associated p-values across our estimations.²⁵ From top to bottom, the three boxes in Table 2 illustrate the results of the OLS estimation and of the two sets of IV estimations, the first one considering

²²Bilateral exchange rates are taken from IFS database; distances are from the CEPII database.

²³We use average unit values in order to minimise the effect of parallel trade potentially in place among the EU members, which could affect the variety market share as well as its price. Since the largest economies in the EU are those included in our dataset, averaging across alternative declarants has the advantage of obtaining the instrument for virtually every variety in the sample. As we show in the next subsection, our tests are suggestive of the validity and reliability of the instrument.

²⁴Table 6 in Appendix B reports the results relative to the coefficients of price and nest share.

²⁵Table 7 in Appendix B reports the value of the GDP coefficients for each estimated equation.

Table 2. Summary of benchmark estimation results: coefficients of log GDP.

Dis Dis		mean	1st quartile	median	3rd quartile
Description Section	OLS				
Description Section	log GDP coefficient	2.620	-0.621	2.636	6.031
observations per equation 31,020 5,904 20,501 36,720 R2 0.79 0.73 0.79 0.86 Share of observations with positive and significant GDP coefficient 88% No. of observations 1,209,783 Share of equations with positive and significant GDP coefficient 69% No. of equations 39 IV1 (non-variety specific instruments) log GDP coefficient 3.006 -0.737 2.255 5.220 log GDP coefficient, p-value 0.141 0.000 0.007 0.217 overidentifying restrictions, p-value 0.319 0.000 0.117 0.728 observations per equation 29,774 5,632 19,547 34,977 R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of equations 2.371 -0.715 2.453 5.912 log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.0	o .	0.043	0.000	0.000	0.000
R2 0.79 0.73 0.79 0.86 Share of observations with positive and significant GDP coefficient 88% No. of observations 1,209,783 Share of equations with positive and significant GDP coefficient 69% No. of equations 39 IV1 (non-variety specific instruments) IV2 (non-variety specific instruments) IV3 (non-variety specific instruments) IV3 (non-variety specific instruments) IV4 (non-variety specific instruments) IV5 (non-variety specific instruments) Occasion of equation of post o	, ,				
Share of observations with positive and significant GDP coefficient 88% No. of observations 1,209,783 Share of equations with positive and significant GDP coefficient 69% No. of equations 39 IV1 (non-variety specific instruments) IVI (non-variety specific instruments) Recovery (non-variety and significant GDP (non) Oweridentifying restrictions, p-value No. of observations with positive and significant GDP coefficient No. of equations Ivi (full set of instruments: non-variety and variety specific instruments) Ivi (full set of instruments: non-variety and variety specific instruments) Ivi (full set of instruments: non-variety and variety specific instruments) Ivi (full set of instruments: non-variety and variety specific instruments) Ivi (full set of instruments: non-variety	observations per equation	31,020	5,904	20,501	36,720
No. of observations 1,209,783 Share of equations with positive and significant GDP coefficient 69% No. of equations 39 No. of equations 39 No. of equations 3,006 -0.737 2,255 5,220 No. of equations 29,774 2,000 0,007 0,217 No. of coefficient, p-value 0,319 0,000 0,117 0,728 0,530 0,53 0,12 0,53 0,53 0,12 0,53 0,53 0,12 0,53 0,53 0,10 0,000 0,007 0,000 0,007 0,000	R2	0.79	0.73	0.79	0.86
Share of equations with positive and significant GDP coefficient 69% No. of equations 39 IVI (non-variety specific instruments) Iog GDP coefficient 3.006 -0.737 2.255 5.220 log GDP coefficient, p-value 0.141 0.000 0.007 0.217 overidentifying restrictions, p-value 0.319 0.000 0.117 0.728 observations per equation 29,774 5,632 19,547 34,977 R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 46% No. of equations 2.371 -0.715 2.453 5.912 log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.0162 observations per equation 24,499 4,570 14,441	Share of observations with positive and	significant G	DP coefficient		88%
No. of equations 39	No. of observations				1,209,783
IV1 (non-variety specific instruments)	Share of equations with positive and significant	gnificant GDP	coefficient		69%
log GDP coefficient 3.006 -0.737 2.255 5.220 log GDP coefficient, p-value 0.141 0.000 0.007 0.217 overidentifying restrictions, p-value 0.319 0.000 0.117 0.728 observations per equation 29,774 5,632 19,547 34,977 R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of observations 1,161,195 Share of equations with positive and significant GDP coefficient 46% No. of equations 39 IV2 (full set of instruments: non-variety and variety specific instruments) log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67	No. of equations				39
log GDP coefficient 3.006 -0.737 2.255 5.220 log GDP coefficient, p-value 0.141 0.000 0.007 0.217 overidentifying restrictions, p-value 0.319 0.000 0.117 0.728 observations per equation 29,774 5,632 19,547 34,977 R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of observations 1,161,195 Share of equations 46% No. of equations 39 IV2 (full set of instruments: non-wariety and variety specific instruments) IV2 (full set of instruments: non-wariety and variety specific instruments) log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0					
No. of observations with positive and significant GDP coefficient 0.000 0.000 0.000 0.000	IV1 (non-variety specific instruments)			
log GDP coefficient, p-value 0.141 0.000 0.007 0.217 overidentifying restrictions, p-value 0.319 0.000 0.117 0.728 observations per equation 29,774 5,632 19,547 34,977 R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of equations 1,161,195 Share of equations with positive and significant GDP coefficient 46% No. of equations 39 IV2 (full set of instruments: non-variety and variety specific instruments) 2,453 5,912 log GDP coefficient 2.371 -0.715 2.453 5,912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 59% <th>log CDD coefficient</th> <th>2.006</th> <th>0.727</th> <th>2.255</th> <th>5 220</th>	log CDD coefficient	2.006	0.727	2.255	5 220
overidentifying restrictions, p-value 0.319 0.000 0.117 0.728 observations per equation 29,774 5,632 19,547 34,977 R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of observations 1,161,195 Share of equations with positive and significant GDP coefficient 46% No. of equations 39 IV2 (full set of instruments: non-variety and variety specific instruments) 2.453 5.912 log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations 955,480 Share of equations with positive and significant GDP coefficient 59% No. of equations 39	_				
R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of observations 1,161,195 Share of equations with positive and significant GDP coefficient 46% No. of equations 39 IV2 (full set of instruments: non-variety and variety specific instruments) 5.912 log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of equations with positive and significant GDP coefficient 59% No. of equations 39	log GDF coemcient, p-value	0.141	0.000	0.007	0.217
R2 0.33 0.12 0.32 0.53 Share of observations with positive and significant GDP coefficient 59% No. of observations 1,161,195 Share of equations with positive and significant GDP coefficient 46% No. of equations 39 IV2 (full set of instruments: non-variety and variety specific instruments) log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of equations with positive and significant GDP coefficient 59% No. of equations 39	overidentifying restrictions, p-value	0.319	0.000	0.117	0.728
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Share of observations with positive and significant GDP coefficient No. of observations Share of equations with positive and significant GDP coefficient No. of equations IV2 (full set of instruments: non-variety and variety specific instruments) Iog GDP coefficient 2.371 -0.715 2.453 5.912 Iog GDP coefficient, p-value 0.073 0.000 0.000 0.001 overidentifying restrictions, p-value 0.120 0.000 0.000 0.000 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient No. of observations 955,480 Share of equations with positive and significant GDP coefficient 59% No. of equations					
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Share of equations with positive and significant GDP coefficient 46% No. of equations 39 IV2 (full set of instruments: non-variety and variety specific instruments) log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of observations with positive and significant GDP coefficient 59% No. of equations 39		significant G	DP coefficient		
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IV2 (full set of instruments: non-variety and variety specific instruments) log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of observations with positive and significant GDP coefficient 59% No. of equations 39		gnificant GDP	coefficient		
log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of observations 955,480 Share of equations with positive and significant GDP coefficient 59% No. of equations 39	No. of equations				39
log GDP coefficient 2.371 -0.715 2.453 5.912 log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of observations 955,480 Share of equations with positive and significant GDP coefficient 59% No. of equations 39	N/2 (full got of instruments, non vori	ate and rapiate	, specific instrum	onts)	
log GDP coefficient, p-value 0.073 0.000 0.000 0.031 overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient 66% No. of observations 955,480 Share of equations with positive and significant GDP coefficient 59% No. of equations 39	1v2 (turi set of firsti uments: non-varie	ety and variety	specific filstrum	ents)	
overidentifying restrictions, p-value 0.120 0.000 0.000 0.162 observations per equation 24,499 4,570 14,441 28,242 R2 0.53 0.38 0.56 0.67 Share of observations with positive and significant GDP coefficient No. of observations 955,480 Share of equations with positive and significant GDP coefficient 59% No. of equations 39	log GDP coefficient	2.371	-0.715	2.453	5.912
observations per equation24,4994,57014,44128,242R20.530.380.560.67Share of observations with positive and significant GDP coefficient66%No. of observations955,480Share of equations with positive and significant GDP coefficient59%No. of equations39	log GDP coefficient, p-value	0.073	0.000	0.000	0.031
observations per equation24,4994,57014,44128,242R20.530.380.560.67Share of observations with positive and significant GDP coefficient66%No. of observations955,480Share of equations with positive and significant GDP coefficient59%No. of equations39					
R20.530.380.560.67Share of observations with positive and significant GDP coefficient66%No. of observations955,480Share of equations with positive and significant GDP coefficient59%No. of equations39					
Share of observations with positive and significant GDP coefficient66%No. of observations955,480Share of equations with positive and significant GDP coefficient59%No. of equations39	observations per equation	24,499	4,570	14,441	28,242
No. of observations955,480Share of equations with positive and significant GDP coefficient59%No. of equations39	R2	0.53	0.38	0.56	0.67
Share of equations with positive and significant GDP coefficient59%No. of equations39	Share of observations with positive and	significant G	DP coefficient		66%
No. of equations 39	No. of observations	955,480			
<u> </u>	Share of equations with positive and si	gnificant GDP	coefficient		59%
	No. of equations				39
Hausman Test, p-value 0.702 0.314 1.000 1.000					

Note. The table reports several moments of the distribution of the estimates of the log of importer's per capita GDP coefficients, based on a separate demand function for each NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. The variety unit value and a nest term (computed as the variety import share for a given product) are included as regressors, along with other determinants of quality, namely: variety, year and importer effects. The component of quality measure unrelated to income is estimated as the sum of these three effects plus the error term. Each panel of the table refers to a different set of regressions: the top panel summarizes the results obtained using the ordinary least square (OLS) estimator; the mid panel those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the bottom panel those obtained with an instrumental variable estimator using the full set of variety and non-variety specific instruments (IV2). The Hansen-Sargan test is used to assess the over-identifying restrictions. The Hausman test assesses the validity of the full set of instruments. Source. Authors' calculations based on the dataset described in Section 3.1.

Table 3. Mean test for log GDP coefficients.

	OLS	IV1	IV2
mean of log GDP coefficient	2.620	3.006	2.371
p-value	0.021	0.006	0.028
no. of observations	39	39	39

Note. Mean test conducted by regressing the log GDP coefficients (originating from the set of estimates summarized in Tables 2 and 6) on a constant, assuming a heteroscedastic distribution of the coefficients. **Source.** Authors' calculations based on the dataset described in Section 3.1.

only non-variety specific instruments (IV1), and the second one with the full set of instruments (IV2). Hereafter, we refer to the IV2 approach as the benchmark estimation, since it deals with endogeneity using a wider set of instruments, thereby providing more efficient estimates.

As expected, the mean of the GDP coefficient is positive in all different estimation strategies, suggesting that richer countries' consumers tend to import higher quality goods from their trade partners. The result of our estimations is not driven by just a few sectors: across the 39 estimated equations, the share of positive and statistically significant GDP coefficients is 59%, and involves 66% of the nearly one million observations in our sample. Table 2 also reports the distribution of the p-values associated to the GDP coefficient estimates. These figures represent the measure of statistical significance for single equations. To assess the joint significance of our GDP coefficients we need to run a formal test, whose results are shown in Table 3, separately for each approach. It is straightforward to notice that all our estimates are significantly different from zero. All statistical exercises thus lend support to our prediction that product quality rises with importer income.

We also conducted a number of exercises to assess the robustness of our results. The first one determines to what extent the Linder hypothesis may bias the quality estimates and, hence, might distort the relationship between quality and income. The Linder hypothesis postulates that countries with similar per capita GDP, displaying similar demand structures, would trade more with each other. In this perspective, any destination country would exhibit an inverse relationship between the market shares captured by exporters from a particular source country and the per capita GDP gap between the two countries. To check whether our results might be mainly driven by this occurrence, we perform again our estimation exercise including as an additional

Table 4. Summary of estimation results: coefficients of log GDP and Linder term.

	mean	1st quartile	median	3rd quartil
OLS				
log GDP coefficient	2.975	-0.958	2.897	6.519
log GDP coefficient, p-value	0.032	0.000	0.000	0.000
Linder term coefficient	-0.385	-0.824	-0.148	-0.002
Linder term coefficient, p-value	0.209	0.000	0.004	0.481
observations per equation	29,810	8	19,775	35,938
R2	0.79	0.74	0.80	0.86
Share of observations with positive and	significant G	DP coefficient		69%
No. of observations				1,162,593
Share of equations with positive and sig	nificant GDP	coefficient		67%
No. of equations				39
IV1 (non-variety specific instruments)	1			
log GDP coefficient	3.830	-0.845	2.563	6.734
log GDP coefficient, p-value	0.163	0.000	0.003	0.200
Linder term coefficient	-1.011	-2.484	-0.459	0.108
Linder term coefficient, p-value	0.322	0.003	0.090	0.580
overidentifying restrictions, p-value	0.295	0.000	0.170	0.573
observations per equation	29,108	5,511	19,158	34,521
R2	0.30	0.07	0.28	0.46
Share of observations with positive and	significant G	DP coefficient		61%
No. of observations				1,135,206
Share of equations with positive and sig	nificant GDP	coefficient		49%
No. of equations				39
IV2 (full set of instruments: non-varie	ty and variety	specific instrum	ents)	
log GDP coefficient	2.459	-1.347	2.686	6.677
log GDP coefficient, p-value	0.068	0.000	0.000	0.017
Linder term coefficient	-1.182	-1.949	-0.367	-0.040
Linder term coefficient, p-value	0.264	0.001	0.042	0.535
overidentifying restrictions, p-value	0.147	0.000	0.000	0.182
observations per equation	23,950	4,474	14,128	27,869
R2	0.50	0.31	0.50	0.68
Share of observations with positive and	significant G	DP coefficient		66%
No. of observations				934,066
Share of equations with positive and sig	nificant GDP	coefficient		59%
No. of equations				39
Hausman Test , p-value	0.736	0.464	0.978	1.000

Note. The table reports several moments of the distribution of the estimates of the coefficients of the log of importer's per capita GDP and of a Linder term (computed as the absolute value of the difference in per capita GDP between importer and exporter), based on a separate demand function for each NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. The variety unit value and a nest term (computed as the variety import share for a given product), are included as regressors, along with other determinants of quality, namely: variety, year and importer effects. The component of quality measure unrelated to income is estimated as the sum of these three effects plus the error term. Each panel of the table refers to a different set of regressions: the top panel summarizes the results obtained using the ordinary least square (OLS) estimator; the mid panel those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the bottom panel those obtained with an in- strumental variable estimator using the full set of variety and non-variety specific instruments (IV2). The Hansen-Sargan test is used to assess the over-identifying restrictions. The Hausman test assesses the validity of the full set of instruments. Source. Authors' calculations based on the dataset described in Section 3.1.

Table 5. Regressions of quality measures on importer's log GDP.

	OLS	IV1	IV2
mean of log GDP coefficient	1.062	0.228	0.830
p-value	0.038	0.007	0.013
constant	-10.944	-2.673	-8.837
p-value	0.039	0.007	0.011
no. of observations	1,209,784	1,161,196	955,481

Note. The table reports the OLS estimates of the coefficients of the log of importer's per capita GDP and of a constant. The dependent variable is a measure of product quality that abstracts from the income component, and is computed as the sum of variety, year and importer effects plus the error term; the results of the set of regressions from which these effects originate are summarized in Table 9. Each column of the table refers to a different regression: the left column summarizes the results obtained using the ordinary least square (OLS) estimator; the mid column those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the right column those obtained with an instrumental variable estimator using the set of variety and non-variety specific instruments (IV2). **Source.** Authors' calculations based on the dataset described in Section 3.1.

regressor a 'Linder term', computed as the absolute value of the difference between the log of per capita GDPs of the relevant importer and exporter. Table 4 reports the results relative to the GDP coefficients and the Linder terms.²⁶ As expected, the Linder term is negative (though, on average, not statistically significant), but its introduction seems to have little influence on the GDP coefficients, which remain positive and significant, and actually exhibit a slight rise in their average magnitudes relative to those delivered by our benchmark exercises.

As a further robustness exercise, we test the relationship between quality and income following a two stage approach. First, we estimate product quality without considering the income term χ_y in (10), in line with the original Khandelwal (2010) specification. Then, we assess the relationship between quality estimates and importer income by means of a OLS regression. Table 5 summarizes the results that we obtain on aggregate.²⁷ Once again, these results show that the relationship between product quality and importer's income per capita is positive and highly significant.

²⁶Table 8 in Appendix B reports the results relative to the coefficients of prices and nest terms.

 $^{^{27}}$ Tables 9 and 10 in Appendix B respectively report the price and nest coefficients of the first-stage estimation and the results relative to the coefficients of log GDP at the sectoral level of the second-stage estimation.

3.3 Discussion

In our estimations, the GDP coefficient captures how our quality measure changes with the log of the importer's per capita income. As such, we can interpret its magnitude in terms of semi-elasticity: that is, a ten percent increase in importer income produces, on average, approximately a 0.23 units rise in product quality.²⁸

Of course, our main interest is actually in whether the estimated magnitude of the GDP coefficient should be considered as sizeable or negligible. As it is often the case with semi-elasticity, pinpointing a benchmark against which to compare the figure would help in obtaining a more transparent assessment. Furthermore, our figure refers to the average of the income semi-elasticities of quality across heterogeneous sectors. In order to get a more reliable assessment, the benchmark should then be determined at the sectoral level, and the average should be computed on the sectoral figures 'standardized' against the relevant benchmarks.

We identify the benchmark as the length of the sectoral quality ladder. A quality ladder is defined as the set of available (or, in this case, observed) qualities in a given market (here, the relevant sector). Its length is measured by the difference between the highest and the lowest quality levels. Divided by the length of the quality ladder, an (appropriately scaled down as above) sectoral GDP coefficient is interpretable as the percentage distance covered by moving from consuming a product to another across the sectoral quality ladder, in response to a given percentage increase in importer income. The resulting sectoral figures are 'adimensional' statistics, hence their mean produces a fairly transparent and reliable indicator of imports' average product quality upgrading as importer income rises.

The newly developed quality upgrading indicator reveals that a ten percent increases in importer income produces a shift of the products consumed across the quality ladders that covers, on average, 2.75% of their length. This implies that an importer that is twice as rich as another enjoys products sitting, on average, in a position 20% higher in the sectoral quality ladders; and that in order for the shift in the product consumed to cover 50% of the quality ladder, an importer should be 5.6 times as rich. Thanks to the quality upgrading indicator,

²⁸Due to the linear-log relationship between product quality and per capita GDP, the figure reported in the text is not obtained by a tenfold reduction of the GDP coefficient: it is scaled down by the factor 0.095. For a formal discussion on how we derive this figure, together with the rest of the auxiliary computations used in this subsection, see Appendix A.3.

we may also deduce more concrete figures. For example, we can infer that the 2013 per capita income distribution interdecile ratio produces a shift in the products imported that covers an average distance across the sectoral qualities ladders of about 56% in France and Germany; 71% in Italy; 74% in Spain; and 68% in the UK. If we dared bringing our quality upgrading indicator out of sample, the average distance covered across the sectoral quality ladders would be ranging from less than 50% in Iceland and Denmark to well over 80% in the United States and Chile.²⁹

Another noteworthy aspect arising from our estimates is that the magnitude of the GDP coefficients is rather varied across sectors. This might be partly due to the fact that, at a 4-digit disaggregation level, products are quite heterogeneous in some sectors; and partly to the mere fact that the dataset is admittedly somewhat noisy. To put things into perspective, we may focus our attention to those sectors where products are relatively 'homogeneous' (*i.e.*, cross-products substitutability is estimated to be relatively high), and demand is 'well-behaved' (*i.e.*, negatively related to the product price): that is, sectors where the nest share coefficient, σ , is estimated to be positive; the price coefficient, α , negative; and both coefficients statistically significant. The share of sectors with positive and significant GDP coefficients raises from 59% to 70% when 'homogeneous' sectors are considered, and up to 83% if we also condition on 'well-behaved' demand.

A further possible reason for the observed heterogeneous magnitude of the GDP coefficients may arise from the sectoral differences in the *scope* for quality upgrading. For example, if higher quality products are relatively inexpensive in a given sector, then there could be more scope for purchasing them even with a limited rise in the importer income, and vice versa. We may think of the length of a sectoral quality ladder *also* as an observable measure of the scope for quality upgrading, since by definition it reveals the largest possible quality range for a given income differential: the one between the richest and the poorer importer.³⁰ In this context, one could expect GDP coefficients to be larger in those sectors exhibiting longer quality ladders. For

²⁹The 2013 interdecile ratios of the income distribution in the cited countries are: 6.9 in France, 6.8 in Germany, 11.4 in Italy, 12.7 in Spain, 10.6 in the UK; and 5 in Iceland, 5.3 in Denmark, 18.5 in the United State, 20.6 in Chile (source: OECD).

³⁰ In terms of primitives, the link between importer income and quality ladder length stems from the connection between the latter (an equilibrium outcome) and the cost of quality upgrading (a technological feature). We give a formal illustration of the relationship between quality ladder length and cost of quality upgrading in Appendix A.3.

the generality of sectors, the correlation between the two variables is however not statistically significant (-0.19 with p-value 0.24). If we condition on 'homogeneous' and 'well-behaved' sectors (in the sense specified above), then the correlation becomes positive and significant (0.75 with p-value 0.005) as expected.

Finally, a note on potentially interesting further development and investigation of the link between product quality and importer income within the framework used in this paper. The theory presented here relies on the assumption that some products are imported because, though inefficiently produced, they meet the idiosyncratic taste of some consumers. Such products are therefore expensive and capture small markets shares, thus are accordingly assigned a low quality level. In the presence of a bell-shaped income distribution in the destination country, however, our empirical results on the link between import quality and importer income are suggestive of a competing explanation for niche products. Although efficiently produced, some top quality products might be so expensive to be affordable only for a thin fraction of rich importers. These products are also assigned a low quality level though, since they command high prices and small (quantitative) market shares. Unfortunately, we are at present unable to disentangle the two groups of products, since the available data include neither end user characteristics of the importer, nor sufficient elements to determine whether the exported goods are efficiently produced.

It should be noted, however, that this caveat should not substantially affect our findings. Failure to identify the quality level of high segment products would in fact shorten the quality ladder, if anything underestimating the scope for quality upgrading. In this perspective, the estimated GDP coefficients might actually be interpreted as a lower bound to the magnitude of the actual link between product quality and importer income. Furthermore, it should be noted that the quality upgrading indicator developed above would be influenced by the identification issue both at the numerator (downward-biased GDP coefficient) and at the denominator (downward-biased quality ladder length). Under the assumption that the two biases are not too disproportionate, one may conjecture that this indicator might provide not only a more transparent figure, but also a more reliable measure of the relationship between import quality and importer income than our estimated GDP coefficients, even at the sectoral level.

4 Conclusion

This paper provides theoretical support and empirical evidence to one of the major issues in the international trade literature: whether quality of imports rises systematically with importer income. Our framework builds on the discrete choice models approach. The novelty of the paper lies in the joint consideration of two results stemming from our framework. First, product quality is income dependent and, in particular, their relationship is positive. Second, our quality measure depend not only on product prices but also on market shares; hence, in our estimations, we depart from the traditional assumption that prices are proxies for quality.

We test our hypothesis on a dataset consisting of import data of five EU countries (namely: France, Germany, Italy, Spain and the UK), and over a 13-year time span, *i.e.*, 1995-2007.

The main contribution of the paper is that we find a positive and significant relationship between the per capita GDP of the selected countries and the alternative quality measure delivered by the model. Our estimates are robust to a number of controls and to three different methodological approaches, based on different instrumental variable strategies.

As an additional contribution, we derive from our estimates a novel, fairly transparent and, under certain assumptions, reliable indicator of import quality upgrading as importer income rises. Based on this indicator, our findings reveal that doubling importer income brings about an average product quality upgrading of 20%, relative to the length of the quality ladders. Looking at the 2013 per capita incomes in our five destination countries, this in turn implies that moving up from the first to the ninth decile of the income distribution generates a 'in-sample' product quality upgrading of about 65% the length of the quality ladders; out-of-sample, that percentage goes up to almost 90% in other OECD countries.

Appendices

A Proof of theoretical results

A.1 Derivation of aggregate demand (2)

Consider the choice of a generic good (j, X) over all possible alternatives in the market, namely $\{(k, Y)\}$, with $k \neq j$ when Y = X. Given (1), the decision rule for consumer i in country M is as follows: consume good (j, X) only if $V_{j, X}^{i, M} > V_{k, Y}^{i, M}$, $\forall (k, Y) \neq (j, X)$. Our task is thus to compute the probability:

$$\Pr\left(j, X | i, M\right) = \Pr\left(\varepsilon_{j, X}^{i, M} > \max_{Y = \{N, S, M\}} \left\{ \max_{k} \left\{ \delta_{k, Y}^{M} + \varepsilon_{k, Y}^{i, M} - \delta_{j, X}^{M} \right\} \right\} \Big|_{(k, Y) \neq (j, X)} \right)$$

The term on the right-hand side represents the joint probability that horizontal differentiation of good (j, X) is valued by consumer i in country M more than that of any other good. We can therefore write:

$$\Pr(j, X | i, M) = \int_{-\infty}^{+\infty} f\left(\varepsilon_{j, X}^{i, M}\right) \exp\left(\int_{k \neq j} \ln\left(\int_{-\infty}^{\varepsilon_{j, X}^{i, M} + \delta_{j, X}^{M} - \delta_{k, X}^{M}} f\left(\varepsilon_{k, X}^{i, M}\right) d\varepsilon_{k, X}^{i, M}\right) dk\right) + \sum_{Y \neq X} \int_{0}^{1} \ln\left(\int_{-\infty}^{\varepsilon_{j, X}^{i, M} + \delta_{j, X}^{M} - \delta_{k, Y}^{M}} f\left(\varepsilon_{k, Y}^{i, M}\right) d\varepsilon_{k, Y}^{i, M}\right) dk\right) d\varepsilon_{j, X}^{i, M}$$

$$(11)$$

where, exploiting the properties of the exponential function, we have expressed the product of a generic sequence z_h as:

$$\prod_{h} z_{h} = \prod_{h} \exp \left(\ln \left(z_{h}\right)\right) = \exp \sum_{h} \left(\ln \left(z_{h}\right)\right)$$

The term $\int_{-\infty}^{\varepsilon_{j,X}^{i,M} + \delta_{j,X}^{M} - \delta_{k,Y}^{M}} f\left(\varepsilon_{k,Y}^{i,M}\right) d\varepsilon_{k,Y}^{i,M}$ is the cumulative distribution function (CDF) of $\varepsilon_{k,Y}^{i,M}$ up to the value $\varepsilon_{j,X}^{i,M} + \delta_{j,X}^{M} - \delta_{k,Y}^{M}$. Since $\varepsilon_{k,Y}^{i,M}$ is a Gumbel random variable, we have:

$$\begin{split} \int_{-\infty}^{\varepsilon_{j,X}^{i,M} + \delta_{j,X}^{M} - \delta_{k,Y}^{M}} f\left(\varepsilon_{k,Y}^{i,M}\right) d\varepsilon_{k,Y}^{i,M} &= & \Pr\left(\varepsilon_{k,Y}^{i,M} < \varepsilon_{j,X}^{i,M} + \delta_{j,X}^{M} - \delta_{k,Y}^{M}\right) \\ &= & \exp\left(-\exp\left(-\left[\varepsilon_{j,X}^{i,M} + \delta_{j,X}^{M} - \delta_{k,Y}^{M}\right]\right)\right) \end{split}$$

Replacing this value into (11) yields:

$$\Pr(j, X | i, M) = \int_{-\infty}^{+\infty} f\left(\varepsilon_{j, X}^{i, M}\right) \exp\left(-\int_{k \neq j} \exp\left(-\left[\varepsilon_{j, X}^{i, M} + \delta_{j, X}^{M} - \delta_{k, X}^{M}\right]\right) dk - \sum_{Y \neq X} \int_{0}^{1} \exp\left(-\left[\varepsilon_{j, X}^{i, M} + \delta_{j, X}^{M} - \delta_{k, Y}^{M}\right]\right) dk\right) d\varepsilon_{j, X}^{i, M}$$

$$(12)$$

Also, the probability density function (PDF) of a Gumbel random variable is:

$$f\left(\varepsilon_{j,X}^{i,M}\right) = \exp\left(-\varepsilon_{j,X}^{i,M} - \exp\left(-\varepsilon_{j,X}^{i,M}\right)\right)$$

Plugging this expression into (12), and rearranging, we obtain:

$$\Pr(j, X | i, M) = \int_{-\infty}^{+\infty} \exp\left(-\varepsilon_{j, X}^{i, M} - \exp\left(-\varepsilon_{j, X}^{i, M}\right) \left[1 + \int_{k \neq j} \exp\left(\delta_{k, X}^{M} - \delta_{j, X}^{M}\right) dk\right] + \sum_{Y \neq X} \int_{0}^{1} \exp\left(\delta_{k, Y}^{M} - \delta_{j, X}^{M}\right) dk\right] d\varepsilon_{j, X}^{i, M}$$

$$= \int_{-\infty}^{+\infty} \exp\left(-\varepsilon_{j, X}^{i, M} - \exp\left(-\varepsilon_{j, X}^{i, M}\right)\right) d\varepsilon_{j, X}^{i, M}$$

$$\cdot \sum_{Y = \{N, S, M\}} \int_{0}^{1} \exp\left(\delta_{k, Y}^{M} - \delta_{j, X}^{M}\right) dk d\varepsilon_{j, X}^{i, M}$$

$$(13)$$

where in the last equation we have exploited the fact that $1 = \exp(0) = \exp\left(\delta_{j,X}^{M} - \delta_{j,X}^{M}\right)$.

Denote:

$$\varpi \equiv \sum_{Y = \{N, S, M\}} \int_0^1 \exp\left(\delta_{k, Y}^M - \delta_{j, X}^M\right) dk$$

and:

$$g\left(\varepsilon_{j,X}^{i,M}\right) \equiv \exp\left(-\varepsilon_{j,X}^{i,M} - \varpi \exp\left(-\varepsilon_{j,X}^{i,M}\right)\right)$$

Note that $g\left(\varepsilon_{j,X}^{i,M}\right)$ is the PDF of a Gumbel random variable with CDF:

$$\exp\left(-\varpi\exp\left(-\varepsilon_{j,X}^{i,M}\right)\right)/\varpi$$

since:

$$\frac{d \exp\left(-\varpi \exp\left(-\varepsilon_{j,X}^{i,M}\right)\right)/\varpi}{d\varepsilon} = -\frac{\exp\left(-\varpi \exp\left(-\varepsilon_{j,X}^{i,M}\right)\right)}{\varpi} \left(-\varpi \exp\left(-\varepsilon_{j,X}^{i,M}\right)\right)$$
$$= \exp\left(-\varepsilon_{j,X}^{i,M} - \varpi \exp\left(-\varepsilon_{j,X}^{i,M}\right)\right) = g\left(\varepsilon_{j,X}^{i,M}\right)$$

Thus, we can use the last equation to rewrite (13) as:

$$\Pr(j, X|i, M) = \frac{1}{\sum_{Y=\{N, S, M\}} \int_0^1 \exp\left(\delta_{k, Y}^M - \delta_{j, X}^M\right) dk} \cdot \left[\exp\left(-\exp\left(-\varepsilon_{j, X}^{i, M}\right) \sum_{Y=\{N, S, M\}} \int_0^1 \exp\left(\delta_{k, Y}^M - \delta_{j, X}^M\right) dk\right)\right]_{-\infty}^{+\infty}$$

where the term in square brackets vanishes since its limit value for $\varepsilon_{j,X}^{i,M} \to +\infty$ equals one, and for $\varepsilon_{j,X}^{i,M} \to -\infty$ equals zero. Finally, we multiply and divide by $\exp\left(\delta_{j,X}^{M}\right)$ to get:

$$\Pr(j, X | i, M) = \frac{\exp\left(\delta_{j, X}^{M}\right)}{\sum_{Y = \{N, S, M\}} \int_{0}^{1} \exp\left(\delta_{k, Y}^{M}\right) dj}$$

Noting that country M has measure ψ_M , integrating over consumers, (2) obtains.

A.2 Derivation of optimality conditions (4) and (5)

Differentiating (3) with respect to p, and setting the resulting expression equal to zero, yields:

$$\left[1 - \alpha \left(p_{j,X}^M - w_X - \frac{q^2}{2A_X}\right)\right] \frac{\psi_M \exp\left(\theta^M q - \alpha p_{j,X}^M\right)}{\sum_{Y = \{M,N,S\}} \int_0^1 \exp\left(\delta_{k,Y}^M\right) dk} = 0$$

simplifying and rearranging, (4) straightforwardly obtains. Differentiating (3) with respect to q, and setting the resulting expression equal to zero, we get:

$$\left[-\frac{q_{j,X}^{M}}{A_{X}} + \theta^{M} \left(p - w_{X} - \frac{\left(q_{j,X}^{M}\right)^{2}}{2A_{X}} \right) \right] \frac{\psi_{M} \exp\left(\theta^{M} q_{j,X}^{M} - \alpha p\right)}{\sum_{Y = \{M,N,S\}} \int_{0}^{1} \exp\left(\delta_{k,Y}^{M}\right) dk} = 0$$

Simplifying this expression returns:

$$\frac{q_{j,X}^M}{A_X} = \theta^M \left(p - w_X - \frac{\left(q_{j,X}^M\right)^2}{2A_X} \right)$$

Using (4) to substitute for $p = p_{j,X}^M$, simplifying and rearranging leads immediately to (5).

For completeness, we might also compute the (average) valuation of good (j, X) in country M. Plugging (4) into the definition of $\delta_{j,X}^{M}$, we have:

$$\delta_{j,X}^{M} = q_{j,X}^{M} \left(\theta^{M} - \frac{\alpha}{2A_{X}} q_{j,X}^{M} \right) - 1 - \alpha w_{X}$$

Then, using (5) to substitute for $q_{j,X}^M$, and rearranging we get:

$$\delta_{j,X}^{M} = \frac{\left(\theta^{M}\right)^{2} A_{X}}{2\alpha} - 1 - \alpha w_{X} \tag{14}$$

We may note that all firms within each source country optimally supply to country M goods that are, on average, equally valued $(\delta_{j,X}^M = \delta_X^M, \forall j)$. Furthermore, by comparing (14) computed for the two countries, it follows that and goods from N are given larger valuation than those from S if

$$\frac{\left(\theta^{M}\right)^{2}\left(A_{N}-A_{S}\right)}{2\alpha} > \alpha\left(w_{N}-w_{S}\right) \tag{15}$$

since either consumers' valuation for quality must be sufficiently high, or technological capabilities in N sufficiently superior, to overcome its disadvantage in manufacturing costs.

A.3 Auxiliary derivations for Section 3.3

GDP coefficients and quality ladder length. Consider a sector s with a quality space of measure λ_s (hereafter, quality ladder length), and suppose that the following relationship between quality (q_s) and per capita GDP (Y) holds at the sectoral level:

$$q_s = \beta_s \ln Y$$

where β_s is a fixed sectoral parameter. For a given change in per capita GDP, say from Y^0 to $Y^1 \equiv gY^0$, quality vary from q_s^0 to q_s^1 according to the expression:

$$\Delta q_s \equiv q_s^1 - q_s^0 = \beta_s \ln Y^1 - \beta_s \ln Y^0 = \beta_s \ln (Y^1 / Y^0) = \beta_s \ln g \tag{16}$$

In the text, we refer to the average value of the GDP coefficient, $\hat{\beta}_s \equiv \mu(\beta_s) = 2.371$, where $\mu(\cdot)$ here denotes the arithmetic mean operator across sectors. By averaging both sides of (16), we obtain:

$$\Delta \hat{q}_s \equiv \mu \left(\Delta q_s \right) = \hat{\beta}_s \ln g$$

Hence, for a 10% growth in per capita GDP (g = 1.1), we have a rise in quality of $\Delta \hat{q}_s = 2.371 \cdot 0.095 = 0.23$ units.

We may 'standardize' (16) by dividing both sides by λ_s , to get:

$$\rho_s \equiv \frac{\Delta q_s}{\lambda_s} = \frac{\beta_s}{\lambda_s} \ln g = \iota_s \ln g$$

where $\iota_s \equiv \beta_s/\lambda_s$. Here, ρ_s can be interpreted as the distance covered by the quality variation relative to the quality ladder length. We can average both sides of the last expression to obtain:

$$\hat{\rho}_s = \hat{\iota}_s \ln g$$

In the data, $\hat{\iota}_s$ is 0.29. Hence, for a 10% growth in per capita GDP (g=1.1), the quality ladder is on average climbed up by $\hat{\rho}_s=0.29\cdot 0.095=2.75\%$. If per capita GDP doubles (g=2), then $\hat{\rho}_s=0.29\cdot 0.69=20\%$. To cover, on average, half of the quality ladder $(\hat{\rho}_s=50\%)$, per capita GDP should grow by the factor $g=e^{\hat{\rho}_s/\hat{\iota}_s}=e^{0.50/0.29}=5.6$.

Regarding the 2013 interdecile ratios of the income distribution in the cited countries, we obtain an average climbing up the quality ladder of about $\hat{\rho}_s = 0.29 \cdot \ln 6.9 = 56\%$ in France, $\hat{\rho}_s = 0.29 \cdot \ln 6.8 = 55.6\%$ in Germany, $\hat{\rho}_s = 0.29 \cdot \ln 11.4 = 71\%$ in Italy, $\hat{\rho}_s = 0.29 \cdot \ln 12.7 = 74\%$ in Spain, $\hat{\rho}_s = 0.29 \cdot \ln 10.6 = 68\%$ in the UK; $\hat{\rho}_s = 0.29 \cdot \ln 5 = 47\%$ in Iceland, $\hat{\rho}_s = 0.29 \cdot \ln 5.3 = 48\%$ in Denmark, $\hat{\rho}_s = 0.29 \cdot \ln 18.5 = 85\%$ in the United States, and $\hat{\rho}_s = 0.29 \cdot \ln 20.6 = 88\%$ in Chile.

Cost of quality upgrading and quality ladder length. In order to explicitly differentiate the cost functions across sectors, let a sectoral parameter ϕ_s (where the subscript s identifies the sector under consideration) enter the cost function, to obtain:

$$\frac{w_X + \phi_s q^2}{2A_X}$$

Differentiating this expression with respect to q and using (5) yields the sectoral measure of the cost of quality upgrading:

$$\lambda_s \equiv \frac{\phi_s \alpha}{A_X}$$

Finally, defining the sectoral quality ladder in a given destination country M as the difference between the highest and the lowest quality levels of the goods imported by M, the model yields $L \equiv \chi_N^M - \chi_S^M$. Using the definition of χ_X^M and once again (5), we may rewrite this expression as:

$$L_{s} \equiv L\left(\phi_{s}, \theta^{M}\right) = \frac{\theta^{M}}{\phi_{s} \alpha} \theta^{M} \left(A_{N} - A_{S}\right) = \frac{1}{\lambda_{s}} \theta^{M} \left(A_{N} - A_{S}\right)$$

It is then immediate to notice the inverse relationship between the length of the ladder L_s and the cost of quality upgrading λ_s : hence, a sector characterized by a lower cost of quality upgrading exhibits a longer quality ladder.

B Additional tables

Table 6. Summary of benchmark estimation results: price and nest coefficients.

	mean	1st quartile	median	3rd quartile
OLS				
price coefficient	-0.003	-0.004	0.000	0.000
price coefficient, p-value	0.058	0.000	0.000	0.001
nest coefficient	0.880	0.833	0.889	0.924
nest coefficient, p-value	0.000	0.000	0.000	0.000
observations per equation	31,020	5,904	20,501	36,720
R2	0.79	0.73	0.79	0.86
Share of observations with negative and	l significant p	rice coefficient		87%
No. of observations				1,209,783
Share of equations with negative and si	gnificant pric	e coefficient		82%
No. of equations				39
IV1 (non-variety specific instruments))			
price coefficient	-0.077	-0.047	-0.007	0.000
price coefficient, p-value	0.288	0.000	0.224	0.576
nest coefficient	0.245	-0.127	0.683	0.910
nest coefficient, p-value	0.110	0.000	0.004	0.106
overidentifying restrictions, p-value	0.319	0.000	0.117	0.728
observations per equation	29,774	5,632	19,547	34,977
R2	0.33	0.12	0.32	0.53
Share of observations with negative and	l significant p	rice coefficient		68%
No. of observations				1,161,195
Share of equations with negative and si	gnificant pric	e coefficient		44%
No. of equations				39
IV2 (full set of instruments: non-varie	ty and variety	y specific instrum	ents)	
price coefficient	-0.003	-0.007	-0.001	0.000
price coefficient, p-value	0.287	0.001	0.129	0.594
nest coefficient	0.526	0.297	0.756	0.995
nest coefficient, p-value	0.045	0.000	0.000	0.013
overidentifying restrictions, p-value	0.120	0.000	0.000	0.162
observations per equation	24,499	4,570	14,441	28,242
R2	0.53	0.38	0.56	0.67
Share of observations with negative and	l significant p	rice coefficient		69%
No. of observations				955,480
Share of equations with negative and si	gnificant pric	e coefficient		44%
No. of equations				39
Hausman Test , p-value	0.702	0.314	1.000	1.000

Note. The table reports several moments of the distribution of the estimates of the coefficients of price and nest term (computed as the variety import share for a given product), based on a separate demand function for each NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. The log of importer's per capita GDP is included as a regressor, along with other determinants of quality, namely: variety, year and importer effects. The component of quality measure unrelated to income is estimated as the sum of these three effects plus the error term. Each panel of the table refers to a different set of regressions: the top panel summarizes the results obtained using the ordinary least square (OLS) estimator; the mid panel those obtained with an instrumental variable estimator using a subset of non-variety specific in- struments only (IV1); the bottom panel those obtained with an instrumental variable estimator using the full set of variety and non-variety specific instruments (IV2). The Hansen-Sargan test is used to assess the over-identifying restrictions. The Hausman test assesses the validity of the full set of instruments. Source. Authors' calculations based on the dataset de-scribed in Section 3.1.

Table 7. Benchmark estimation results: coefficients of log GDP by 4-digit sector.

Sector (NACE-4)	OLS	IV1	IV2	
1512	4.842 ***	2.715 ***	1.715	
1520	0.680 ***	0.746 ***	1.061 ***	
1541	-2.241 ***	-4.581 **	-5.748 ***	
1542	-0.107	-0.701	-0.618	
1581	6.031 ***	5.761 ***	5.912 ***	
1582	-4.806 ***	-5.249	-3.091 *	
1584	0.917 ***	0.464	1.113 ***	
1585	-5.837 ***	-4.237 ***	-4.351 ***	
1586	2.677 ***	2.255	2.453 ***	
1587	-0.621 **	-1.213	-0.715	
1588	8.895 ***	9.025 ***	7.596 ***	
1591	-4.194 ***	-12.247 ***	-9.977 ***	
1593	30.697 ***	24.883 ***	30.066 ***	
1594	2.886 ***	2.595	4.088 ***	
1595	9.823 ***	21.751	12.209	
1596	5.517 ***	0.617	1.641	
1597	-6.547 ***	-7.866 **	-8.037 ***	
1598	3.298 ***	3.891 ***	3.396 ***	
1600	-3.452 ***	-2.111	-3.861	
1751	2.537 ***	2.457 ***	2.789 ***	
1753	0.035	-0.341	0.203	
1760	0.656 ***	2.642 ***	3.254 ***	
1771	-10.003 ***	0.000 ***	-9.971	
1772	8.569 ***	8.537 ***	8.652 ***	
1810	1.709 ***	1.875 ***	1.758 ***	
1821	8.332 ***	6.552 ***	7.615 ***	
1822	0.560 ***	-0.737 ***	-0.275 **	
1823	12.527 ***	13.477 ***	12.962 ***	
1824	3.341 ***	5.220 ***	3.545 ***	
1910	6.584 ***	13.651 ***	9.542 ***	
1920	2.870 ***	3.552 ***	3.054 ***	
2224	-4.043 ***	-2.278	-5.001 **	
2441	8.967 ***	-0.016	8.107 ***	
2451	3.565 ***	5.023 **	3.374 ***	
2452	2.835 ***	4.197 ***	2.821 ***	
3541	1.831 ***	0.975	1.154 **	
3542	-7.068 ***	-5.894 ***	-6.193 ***	
3615	7.287 ***	19.492	7.697 ***	
3640	2.636 ***	2.339 ***	2.512 ***	

Note. The table reports the estimated coefficients of the log of importer's per capita GDP for each demand function at the NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. The variety unit value and a nest term (computed as the variety import share for a given product) are included as regressors, along with other determinants of quality, namely: variety, year and importer effects. The component of quality measure unrelated to income is estimated as the sum of these three effects plus the error term. Each column of the table refers to a different set of regressions: the left column summarizes the results obtained using the ordinary least square (OLS) estimator; the mid column those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the right column those obtained with an instrumental variable estimator, using the full set of variety and non-variety specific instruments (IV2). Asterisks denote level of significance of the null hypothesis (coeff = 0) of 10% (*), 5% (**) or 1% (***). Source. Authors' calculations based on the dataset described in Section 3.1.

Table 8. Summary of estimation results with Linder term: price and nest coefficients.

	mean	1st quartile	median	3rd quartile
OLS				
price coefficient	-0.003	-0.004	0.000	0.000
price coefficient, p-value	0.062	0.000	0.000	0.001
nest coefficient	0.878	0.830	0.887	0.920
nest coefficient, p-value	0.000	0.000	0.000	0.000
observations per equation	29,810	8	19,775	35,938
R2	0.79	0.74	0.80	0.86
Share of observations with negative an	nd significant p	rice coefficient		87%
No. of observations				1,162,593
Share of equations with negative and	significant pric	e coefficient		82%
No. of equations				39
IV1 (non-variety specific instrument	s)			
price coefficient	-0.055	-0.065	-0.007	0.001
price coefficient, p-value	0.261	0.002	0.188	0.532
nest coefficient	0.210	-0.700	0.547	0.963
nest coefficient, p-value	0.187	0.000	0.005	0.334
overidentifying restrictions, p-value	0.295	0.000	0.170	0.573
observations per equation	29,108	5,511	19,158	34,521
R2	0.30	0.07	0.28	0.46
Share of observations with negative an	nd significant p	rice coefficient		69%
No. of observations				1,135,206
Share of equations with negative and	significant pric	e coefficient		44%
No. of equations				39
IV2 (full set of instruments: non-var	iety and variety	specific instrum	ents)	
price coefficient	-0.009	-0.006	-0.001	0.000
price coefficient, p-value	0.317	0.003	0.127	0.700
nest coefficient	0.459	0.251	0.772	0.996
nest coefficient, p-value	0.057	0.000	0.000	0.039
overidentifying restrictions, p-value	0.147	0.000	0.000	0.182
observations per equation	23,950	4,474	14,128	27,869
R2	0.50	0.31	0.50	0.68
Share of observations with negative an	nd significant p	rice coefficient		70%
No. of observations	934,066			
Share of equations with negative and	significant pric	e coefficient		44%
No. of equations				39
Hausman Test , p-value	0.736	0.464	0.978	1.000

Note. The table reports several moments of the distribution of the estimates of the coefficients of price and nest term (computed as the variety import share for a given product), based on a separate demand function for each NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. The log of importer's per capita GDP and a Linder term (computed as the absolute value of the difference in per capita GDP between importer and exporter) are included as regressors, along with other determinants of quality, namely: variety, year and importer effects. The component of quality measure unrelated to income is estimated as the sum of these three effects plus the error term. Each panel of the table refers to a different set of regressions: the top panel summarizes the results obtained using the ordinary least square (OLS) estimator; the mid panel those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the bottom panel those obtained with an instrumental variable estimator using the full set of variety and non-variety specific instruments (IV2). The Hansen-Sargan test is used to assess the over-identifying restrictions. The Hausman test assesses the validity of the full set of instruments. Source. Authors' calculations based on the dataset described in Section 3.1.

Table 9. Estimation results without GDP regressor: price and nest coefficients.

	mean	1st quartile	median	3rd quartil
OLS				
price coefficient	-0.003	-0.004	0.000	0.000
price coefficient, p-value	0.053	0.000	0.000	0.001
nest coefficient	0.878	0.836	0.889	0.920
nest coefficient, p-value	0.000	0.000	0.000	0.000
observations per equation	31,020	5,904	20,501	36,720
R2	0.78	0.73	0.79	0.85
Share of observations with negative and	l significant p	rice coefficient		87%
No. of observations				1,209,784
Share of equations with negative and si	gnificant pric	e coefficient		85%
No. of equations				39
IV1 (non-variety specific instruments))			
price coefficient	-0.096	-0.057	-0.012	-0.001
price coefficient, p-value	0.258	0.000	0.140	0.414
nest coefficient	0.260	-0.132	0.684	0.944
nest coefficient, p-value	0.113	0.000	0.005	0.187
overidentifying restrictions, p-value	0.304	0.000	0.052	0.704
observations per equation	29,774	5,632	19,547	34,977
R2	0.33	0.11	0.30	0.54
Share of observations with negative and	l significant p	rice coefficient		70%
No. of observations				1,161,196
Share of equations with negative and si	gnificant pric	e coefficient		46%
No. of equations				39
IV2 (full set of instruments: non-varie	tv and variety	specific instrum	ents)	
price coefficient	-0.003	-0.007	-0.002	0.000
price coefficient, p-value	0.275	0.001	0.077	0.536
nest coefficient	0.535	0.205	0.807	1.003
nest coefficient, p-value	0.044	0.000	0.000	0.008
overidentifying restrictions, p-value	0.127	0.000	0.000	0.073
observations per equation	24,500	4,570	14,441	28,242
R2	0.52	0.40	0.56	0.67
Share of observations with negative and	l significant p	rice coefficient		72%
No. of observations				955,481
Share of equations with negative and si	gnificant pric	e coefficient		46%
No. of equations				39
Hausman Test , p-value	0.722	0.471	0.975	1.000

Note. The table reports several moments of the distribution of the estimates of the coefficients of price and nest term (computed as the variety import share for a given product), based on a separate demand function for each NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. Regressors also include the determinants of quality, namely: variety, year and importer effects (and do NOT include an importer GDP term). Quality is estimated as the sum of these three effects plus the error term. Each panel of the table refers to a different set of regressions: the top panel summarizes the results obtained using the ordinary least square (OLS) estimator; the mid panel those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the bottom panel those obtained with an instrumental variable estimator using the full set of variety and non-variety specific instruments (IV2). The Hansen-Sargan test is used to assess the over-identifying restrictions. The Hausman test assesses the validity of the full set of instruments. Source. Authors' calculations based on the dataset described in Section 3.1.

Table 10. Regressions of quality measures on importer's log GDP by 4-digit sector.

Sector (NACE-4)	OLS	IV1	IV2	
1512	0.242 ***	-1.564 ***	-1.663 ***	
1520	-0.648 ***	-1.215 ***	-1.149 ***	
1541	0.171	-4.115 ***	-2.760 ***	
1542	0.959 ***	2.390 ***	1.973 ***	
1581	1.409 ***	1.166 ***	1.374 ***	
1582	0.670 ***	-11.907 ***	6.054 ***	
1584	0.631 ***	0.749 ***	0.806 ***	
1585	2.041 ***	1.393 ***	1.490 ***	
1586	-0.098	0.926 ***	1.330 ***	
1587	1.158 ***	1.847 ***	0.717 ***	
1588	1.928 ***	1.556 ***	1.762 ***	
1591	1.310 ***	0.344	0.599 **	
1593	5.777 ***	4.969 ***	4.928 ***	
1594	0.571 ***	0.727 ***	0.781 ***	
1595	4.310 ***	5.087 ***	4.368 ***	
1596	-0.580 ***	-0.943 ***	-0.837 ***	
1597	-1.657 ***	-1.744 ***	-1.806 ***	
1598	1.983 ***	2.760 ***	2.377 ***	
1600	2.469 ***	0.637	-5.435 ***	
1751	-0.515 ***	-0.818 ***	-0.401 ***	
1753	0.077	-0.479 ***	0.014	
1760	-0.040	-3.297 ***	-2.839 ***	
1771	4.221 ***	-6.453	-0.753	
1772	2.309 ***	1.717 ***	1.753 ***	
1810	0.079	0.062	0.049	
1821	-1.215 ***	-1.643 ***	-1.024 ***	
1822	2.403 ***	0.900 ***	1.688 ***	
1823	1.576 ***	2.244 ***	2.903 ***	
1824	-0.113 ***	-1.837 ***	-0.771 ***	
1910	6.383 ***	9.609 ***	7.264 ***	
1920	0.041	-0.222 ***	-0.286 ***	
2224	0.198	1.306 ***	1.160 ***	
2441	-1.639 ***	-1.660 **	-2.133 ***	
2451	0.986 ***	1.135 ***	1.546 ***	
2452	1.236 ***	-0.886 ***	1.275 ***	
3541	2.357 ***	2.464 ***	2.523 ***	
3542	1.781 ***	1.421 ***	1.545 ***	
3615	1.620 ***	5.797 ***	1.981 ***	
3640	-0.875 ***	-0.951 ***	-0.945 ***	

Note. The table reports the estimated coefficients of the log of importer's per capita GDP for each demand function at NACE 4-digit sector. The dependent variable is the log of the variety market share in a given sector. A variety is defined as a product (according to the NACE 8-digit classification) imported from a given country. The variety unit value, a nest term (computed as the variety import share for a given product), and a Linder term (computed as the absolute value of the difference in per capita GDP between importer and exporter) are included as regressors, along with other determinants of quality, namely: variety, year and importer effects (and do NOT include an importer GDP term). Quality is estimated as the sum of these three effects plus the error term. Each column of the table refers to a different set of regressions: the left column summarizes the results obtained using the ordinary least square (OLS) estimator; the mid column those obtained with an instrumental variable estimator using a subset of non-variety specific instruments only (IV1); the right column those obtained with an instrumental variable estimator using the full set of variety and non-variety specific instruments (IV2). Asterisks denote level of significance of the null hypothesis (coeff = 0) of 10% (*), 5% (**) or 1% (***). **Source.** Authors' calculations based on the dataset described in Section 3.1.

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