Weight-Based Quality Specialization

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Abstract

This paper uncovers a new type of quality specialization that occurs along the *physical weight* margin. To this end, I document that (i) there is great heterogeneity in the unit weight of traded goods even within narrowly-defined product categories; (ii) heavier varieties of the same product are more costly to produce; (iii) heavier varieties exhibit (on average) a higher product appeal or quality; and (v) the cost of transportation increases more rapidly with unit weight than the cost of production. These observations indicate that suppliers face a basic *quality/cost* trade-off when choosing their output unit weight. As a result of this trade off, high-wage economies specialize in heavier varieties of a given good, while geographically distant economies specialize in lighter varieties (i.e., *weight-based quality specialization*). Micro-level trade data support these predictions and suggest that weight-based quality specialization can explain a significant portion of the cross-national variation in export prices and export quality. Moreover, accounting for the heterogeneity in export unit weights yields support for iceberg trade cost assumption, which has proven to be elusive in the past.

1 Introduction

An accumulating body of evidence over the past two decades has established that international specialization occurs predominantly *within* rather than *across* product categories. Concurrent with the evidence, there has been a surge in new theories of within-industry specialization. The dominant view underlying these theories is that different countries specialize in low- or high-quality varieties of the same product.

For all their merits, mainstream theories of quality specialization have paid less attention to the determinants of product quality. Existing theories typically model product quality as a one-dimensional, over-arching demand shifter. As noted by Eaton and Fieler (2019) this one-dimensional approach to modeling product quality can limit predictive power in many instances. Furthermore, improving on this approach seems feasible in light of recent research on consumer psychology, which suggests that perception of quality is related to tangible product characteristics that are often observable in the data (Jostmann et al. (2009))

In this paper, I analyze one such overlooked but readily-observable determinant of product quality: *physical weight*. My analysis is inspired by an extensive body of research on consumer psychology, which suggests that consumer's perception of quality is strongly linked to a product's physical weight. The same wine or perfume is perceived as higher quality when presented in a heavier bottle (Piqueras-Fiszman and Spence (2012)); heavier vehicles are perceived as safer vehicles (Thomas and Walton (2008)); and metal credits cards are perceived as more luxurious relative to their plastic counterparts (Lindstrom (2006)). More revealing, van Rompay et al. (2014) have analyzed consumer's perception of quality using dummy phones for which product weight is manipulated independently from product appearance. They find that consumers perceive the identical-looking heavier phones as higher quality.

I estimate product quality using detailed trade data, and show that quality increases with physical weight for the vast majority of product categories.[1] I also document that heavier varieties of the same product are more costly to produce and transport. These findings indicate that firms face a basic *quality/cost* trade-off when choosing the optimal weight of their output. This previously-overlooked trade-off induces low-wage and remote countries to specialize in lighter (lower-quality) varieties of the same product. I label this type of specialization as *weight-based quality specialization* and show that it accounts for a large portion of the cross-national variation in export price and quality.

In Section 2, I use micro-level trade data from the U.S. and Colombia to document a set of new regularities regarding the physical unit weight of traded goods. My analysis concerns indivisible or discrete goods like "Transport Equipment," "Machinery," and "Electronics & Appliances," which (i) account for more than 50% of global trade and (b) come with a pre-determined factory gate unit weight. Customs data typically reports the count (Q) and the net weight (W) of the discrete goods in each import shipment. Using this information, I compute the unit weight (W/Q) of the imported goods and document the following five regularities:

1. There is a significant amount of heterogeneity in the physical unit weight of traded goods even within narrowly-defined categories. To give an example, in product code "HS8525802000,"[2] a Nikon D800 camera weighs 3-times that of the

[1] Quality, in my analysis, encompasses product attributes that increase the consumer appeal of a product given its price. It is inferred from a demand function fitted to observable quantity and price data—a method that is inspired by Khandelwal (2010) and Hummels and Klenow (2005).

[2] The verbal description of this product is *"Digital Cameras and Video Camera Recorders."*

Nikon D3300, which is manufactured and supplied by the same company.

2. Heavier varieties of the same product are more costly to produce. Referring to the previous example, the 3-times heavier Nikon D800 exhibits a price that is around 5-times higher than the Nikon D3300. This price difference is partly reflective of the heavier unit requiring more raw inputs. As one may expect, the positive weight-cost relationship is violated in a few product categories, like "Road Bicycles" and "Sleepwear," but it is significant in well over 95% of the HS10 product categories. Even more revealing, close to 70% of the within-product price heterogeneity can be attributed to differences in physical weight.[3]

3. Heavier varieties are not only more costly to transport, but the cost of transportation raises more rapidly with physical weight than the cost of production. Based on my estimates, across all discrete product categories, a 10% increase in the unit weight of output increases the marginal production cost by 7% and the unit transport cost by more than 13%. Transportation costs also increase with the value-to-weight ratio of the transported goods, but at an elasticity that is well below one.

4. The iceberg formulation provides a semi-accurate, reduced-form representation of the fact that transport costs increase with both the *unit weight* and *value-to-weight ratio* of transported goods. To be specific, mainstream trade theories do not formally model the *unit weight* or the *value-to-weight ratio* of the traded goods. Instead, they model the unit transport cost as being proportional to *unit price=value-to-weight×unit weight*. This reduced-form characterization is known as the iceberg cost formulation. Given that transport costs (i) increase more-than-proportionally with *unit weight*, but (ii) increase less-than-proportionally with *value-to-weight*, they can be crudely modeled as a cost that increases proportionally with *unit price*. When formally estimated, the elasticity of the unit transport cost with respect to unit price is not exactly "one" (as implied by the iceberg assumption), but fairly close to "one."

5. Heavier varieties of the same product exhibit a significantly higher quality or appeal, with unit weight explaining up to 60% of the cross-supplier variation in quality. This observation is documented with quality levels estimated using the Khandelwal (2010) methodology.[4] Importantly, it also aligns with the extensive body of psychology research reviewed earlier. In the case of my previous example, the heavier Nikon D800 is perceived as a higher quality camera compared to

[3] An HS10 product is a 10-digit classification of products based on the Harmonized System.

[4] Khandelwal's (2010) methodology for measuring product quality is akin to the methodology developed earlier by Hummels and Klenow (2005). The connection between these two approaches is detailed in Appendix C. This paper simply extends and applies this technique to firm-level trade data.

the lighter D3300 model. The more surprising aspect of the observation is that physical unit weight explains up to 60% of the cross-supplier variation in output quality, whereas value-to-weight ratios explain less than 30% of the variation.[5]

Section 3 develops a simple model to study the firms' choice of output unit weight. My theory is based on four primitive assumptions: (*i*) output quality is increasing in physical weight as well as intangible attributes like design or marketing that increase the value-to-weight ratio independent of physical weight; (*ii*) the unit transport cost increases more rapidly with unit weight than the marginal production cost; (*iii*) transportation employs labor in both the origin and destination countries; and (*iv*) transportation costs increase with geographical distance.

In this setup, firms choose their output unit weight to maximize profits in each market. The firm's choice is subject to a of basic trade-off: On one hand, by increasing the physical weight of their output variety, firms can increase their product appeal and sales. On the other hand, producing heavier varieties involves using more raw inputs and paying a higher transport cost.

Facing this trade-off, firms located in high-wage economies specialize in the production of heavier varieties. To the extent that heavier varieties are of higher quality, one can perceive this pattern as *weight-based* quality specialization. At the same time, we know from the existing literature that high-wage economies also specialize in intangible dimensions of quality, which increases the value-to-weight ratio of their output conditional on unit weight. That being the case, *weight-based* quality specialization reinforces the other dimensions of quality specialization in high-wage economies.

Firms located in distant economies, meanwhile, specialize in lighter varieties to circumvent the distance-increasing transport costs. At the same time, due to the "Washington Apples Effect", distant economies tend to upgrade their quality along the intangible dimension in order to increase the value-to-weight ratio of their output. So, in the case of distant economies, *weight-based* quality specialization countervails the *Washington Apples-driven* quality specialization.

Section 4 presents empirical support for the above predictions. Specifically, the unit weight of country-level exports increases significantly with the exporter's GDP per capita, but decreases with bilateral distance between the trading partners. The value-to-weight ratio of exports, meanwhile, increases significantly with both the exporter's GDP per capita and bilateral distance. Considering this, the effect of GDP per capita on the export unit price (p=*value-to-weight*$\times$*unit weight*) is always positive, whereas the effect of distance on export unit price depends on the relative force of the *weight-based* versus *Washington Apples-driven* quality specialization.

[5] My estimates indicate that the unit weight and value-to-weight ratio of output, together, explain around 90% of the variation in output quality in both the Colombia and U.S. samples.

These findings contribute to a growing literature that studies the anatomy of within-industry specialization (Schott (2004); Hummels and Klenow (2005); Hallak (2006); Khandelwal (2010); Baldwin and Harrigan (2011); Crozet et al. (2012); Johnson (2012); Lugovskyy and Skiba (2014); Feenstra and Romalis (2014); Sutton (2012); and Dingel (2016)). The existing literature has generally emphasized quality specialization, as a means to explain the tremendous heterogeneity in export price levels within narrowly-defined industries. I argue that a significant amount of the observed price heterogeneity can be explained by weight-based quality specialization.

This paper is also related to a large literature investigating international transport costs (Clark et al. (2004); Hummels and Skiba (2004); Hummels (2007); Blonigen and Wilson (2008); Hummels et al. (2009); Abe and Wilson (2009)). My contribution to this literature is two-fold. The first contribution is highlighting *unit weight* as a key determinant of the unit transport cost.[6] The second contribution is using detailed firm-level data to shed fresh light on the determinants of transport costs—in comparison, the prior literature on this topic has mostly relied on country-level data.

Very few studies have directly emphasized physical weight as a driver of international specialization. Alfred Weber's classic theory of location choice emphasized that the physical weight of raw material versus final goods determines the optimal location of production. More recently, Duranton et al. (2014) have shown that cities with more highways specialize in sectors producing heavy goods. Relatedly, Harrigan (2010) argues that distant suppliers have a comparative advantage in lighter goods; but instead of directly using data on physical unit weight, he classifies light and heavy goods based on value-to-weight ratios.

Finally, the results in this paper present an avenue of optimism for the iceberg trade cost specification. Ever since Samuelson (1954), the aforementioned specification has been widely employed in the quantitative trade literature to preserve multiplicative separability. Recently, though, the iceberg assumption has come under criticism based on evidence derived from actual transport cost data. This paper shows that once we account for the heterogeneity in unit weights, transport costs are quasi-iceberg for discrete goods, which are responsible for more than 50% of global trade.

[6]Due to data limitations, prior analyses of transport costs did not explicitly control for unit weight. Hummels and Skiba (2004), for instance, only observed data on the total weight of the traded goods (W), but not total quantity (Q). As a result, they assumed that unit weight (W/Q) is uniform within HS10 product categories to infer Q from W. Relatedly, Clark et al. (2004) estimate how the *total* weight of a shipment affects the *total* transportation charge, but this approach does not disentangle the *unit weight* effect from the scale effects.

2 The Effect of Physical Weight on Cost and Quality

I begin my analysis by uncovering five basic facts concerning the dependence of production cost, transportation cost, and quality on physical weight. I document these facts using two distinct data-sets. The first is firm-level data on the universe of Colombian import transactions. The second is country-level data on the universe of US imports. This latter data-set, which is publicly-available and widely-used, allows me to cross-validate the findings produced with the firm-level data.

Firm-Level Import Data from Colombia. My main dataset covers the universe of Colombian import transactions for the 2007–2013 period. The data has been collected and made available by the National Tax Agency. For each import transaction, it identifies the exporting firm's id, the Colombian municipality responsible for the import order, the 10-digit Harmonized System (HS10) classification to which the imported goods belong, as well as the f.o.b. value, freight cost, insurance charge (all in US dollars), quantity and net weight of the imported goods. Altogether, the Colombia data features 7,296 distinct HS10 product categories, and 226,288 firms from 251 different countries

I index each observation in the Colombia sample with $\boldsymbol{s, jkt}$, where s ***denotes an individual shipment exported by firm*** j***, consisting of goods pertaining to HS10 product category*** k ***in year*** t. The main distinction between shipments from supplier j of product k in year t is that they are possibly ordered by different entities, located in different municipalities within Colombia. Considering this choice of notation, $V_{s,jkt}$, $T_{s,jkt}$, $W_{s,jkt}$, and $Q_{s,jkt}$ denote the total f.o.b. value, the total freight charge, the total physical weight, and the total quantity of goods pertaining to observation s, jkt.

Country-Level Import Data from the US. The publicly-available US import data is compiled and updated by Schott (2008), and reports all US import transactions for the 1995-2015 period.[7] All transactions, in a given year, are aggregated up and reported at the level of *exporting country*×*HS10 product*×*district of entry*. Among other statistics, each data point reports the total f.o.b. value, freight charges, quantity, and the net physical weight of the imported goods. This data features around 17,000 distinct HS10 product categories, and 42 distinct US districts importing from 238 different countries.

In the case of the US data $\boldsymbol{s, jkt}$, indexes ***an aggregate export shipment arriving in district*** s ***from country*** j***, consisting of goods belonging to HS10 product category*** k ***in year*** t. Accordingly, $V_{s,jkt}$, $T_{s,jkt}$, $W_{s,jkt}$, and $Q_{s,jkt}$ denote the total f.o.b. value, the total freight charge, the total physical weight, and the total quantity of goods pertaining to observation s, jkt.

[7] The data can be also downloaded directly from the Census website (see *http://www.census.gov/foreign-trade*). A monthly version of the data is also available for certain years.

Restricting the Sample to Discrete Goods. Since my analysis here concerns the role of product weight, I restrict both samples to only "discrete" goods. That is, goods that are countable and exhibit a pre-determined factory-gate unit weight. Such goods typically belong to the "Transport Equipment," "Electronics & Appliances," and "Machinery" sectors. Trimming the sample to only include discrete goods is done using information on the "units" in which quantity is reported. For discrete goods, quantity is reported in terms of the *number of goods*, whereas for non-discrete goods quantity is usually reported in terms of kilograms. Table 1 displays the share of discrete goods in each industry. Appendix A provides a more detailed description of trimming the data based on the discrete/non-discrete criteria. Restricting the final sample to discrete goods leaves me with around 8,299,000 observations spanning around 2,900 HS10 categories in the firm-level Colombia sample, and around 4,701,000 observations spanning 5,445 HS10 product categories in the country-level US sample.[8]

Table 1: The share of discrete goods in total imports

	Colombia Sample		**US Sample**	
Industry	Share of discrete goods	Industry's share in total imports	Share of discrete goods	Industry's share in total imports
Transport Equipment	100%	18.2%	92.5%	19.4%
Machinery	99.6%	16.1%	98.0%	12.3%
Electrical & Optical Equipment	93.1%	7.7%	98.4%	13.6%
N.E.C. & Recycling	90.8%	1.4%	54.5%	2.8%
Rubber & Plastic	70.3%	3.7%	51.5%	1.6%
Textiles, Leather & Footwear	52.5%	5.1%	88.7%	9.8%
Minerals	35.7%	1.2%	32.8%	1.1%
Wood	22.1%	0.2%	9.8%	1.5%
Paper	15.6%	2.2%	18.2%	2.3%
Basic & Fabricated Metals	14.7%	8.9%	7.9%	6.6%
Food	1.6%	5.6%	1.5%	3.8%
Agriculture & Mining	1.4%	5.2%	2.1%	13.6%
Chemicals	0%	19%	1.6%	8.1%
Petroleum	0%	6%	0%	3.4%
All Industries	50.6%	100%	56.3%	100%

Note: All percentage shares are value-weighted. The sectoral classification is from the WIOD. Observations that report quantity in units of "count" are classified as discrete.

[8]The higher number of HS10 codes in the US sample is partly reflective of the change in HS10 codes over time. In the course of 1995-2015 many existing HS10 codes where rendered obsolete and many new HS10 codes where introduced—see Pierce and Schott (2012). The change in HS10 codes will not prove problematic for my analysis, as I conduct all the estimations with product-year (or more narrowly-defined) fixed effects.

2.1 Empirical Regularities

For each observation s, jkt (shipment $s \times$supplier $j \times$HS10 product $k \times$ year t) I observe information on total physical weight, $W_{s,jkt}$, total quantity, $Q_{s,jkt}$, total f.o.b. value, $V_{s,jkt}$, and total transport charge (freight plus insurance), $T_{s,jkt}$. With this information, I can calculate the following statistics:

1. [*unit weight*] $\omega_{s,jkt} = W_{s,jkt} / Q_{s,jkt},$;
2. [*f.o.b. unit price*] $p_{s,jkt} = V_{s,jkt} / Q_{s,jkt}$;
3. [*value-to-weight ratio*] $v_{s,jkt} = V_{s,jkt} / W_{s,jkt}$;
4. [*unit transport cost*] $\tau_{s,jkt} = T_{s,jkt} / Q_{s,jkt}$.

It is worth repeating that in the Colombia sample the unit of supply is a firm, whereas in the US sample the unit of supply is a country. Hence, the supplier index j denotes a firm in the Colombia sample but a country in the US sample. After constructing the above variables, I document five basic facts concerning the heterogeneity in unit weight and its effect on production cost, transportation cost, and product quality.

FACT 1. *There is tremendous heterogeneity in the unit weight of traded goods, even within narrowly-defined categories*

Table 2 reports the within-supplier×product×year variation in import unit weights for each sample. In the median *firm–product–year* cell in the Colombia sample, the heaviest (75 percentile) item imported by Colombia weighs 1.5-times more than the lightest (25 percentile) item. In the US sample, the unit of supply is a country, so one may expect even more within-supplier heterogeneity. For the median *country–product–year* cell in this sample, the heaviest (75 percentile) item imported by the US weighs 1.8-times more than the lightest (25 percentile) item. Looking at other metrics of heterogeneity, such as the coefficient of variation, draws similar conclusions.

One may suspect that the sizable variation in unit weights is mere noise. In what follows, I present additional facts indicating that the variation in unit weights is systematic.

FACT 2. *Heavier varieties of a given product are more costly to produce, with unit weight explaining more of than 60% of the within-product variation in unit prices.*

To establish this fact, I assume that supplier j charges the same price-markup on different varieties of the same HS10 product in a given year. To elaborate, the unit price of each shipment can be decomposed into a markup component, μ, and a marginal cost component, mc. My assumption is that the markup component can be treated as a

Table 2: The within product-supplier heterogeneity in unit weight

	Median	1st quartile	3rd quartile
	Colombia (within *firm-product-year*)		
75-25 pct ratio	1.51	1.12	3.06
coefficient of variation	40%	13%	98%
	U.S. (within *country of origin-product-year*)		
75-25 pct ratio	1.76	1.31	3.78
coefficient of variation	57%	29%	129%

Note: The statistics in this table exclude single-observation exporters. In the case of Colombia, that is firm-product-year cells with a single observation. In the case of the US, that is country-product-year cells with a single observation.

supplier×product×year fixed effect. Namely,

$$p_{s,jkt} = \mu_{jkt} \times mc_{s,jkt}.$$

Under this assumption, I can identify $\alpha \equiv \partial \ln mc / \partial \ln \omega$ by running the following regression,[9]

$$\ln p_{s,jkt} = \alpha \ln \omega_{s,jkt} + \delta_{jkt} + \epsilon_{s,jkt}, \tag{1}$$

where $\epsilon_{s,jkt}$ accounts for shipment-specific –non-weight related– variations in the marginal cost plus measurement errors; and δ_{jkt} controls for supplier-product-year fixed effects.[10] Under our earlier assumption, δ_{jkt} also absorbs all the markup variation. Accordingly, the variation in $p_{s,jkt}$ conditional on δ_{jkt} is reflective of the variation in $mc_{s,jkt}$. The estimated elasticity α can, thus, be interpreted as the elasticity of marginal cost with respect to weight, i.e., $\alpha = \partial \ln mc / \partial \ln \omega$.

Section 2.2 presents a more in depth discussion of my assumption on markup heterogeneity. Note, however, that Fact 2 can be stated as is, even if markups are heterogeneous within supplier-product-year cells as long as $\partial \ln \mu / \partial \ln \omega < \partial \ln p / \partial \ln \omega$. The same goes for Fact 3 that is presented subsequently. However, in the presence of within-cell markup heterogeneity, the estimated $\alpha \equiv \partial \ln \mu / \partial \ln \omega + \partial \ln mc / \partial \ln \omega$ can no longer be interpreted as the elasticity of marginal cost with respect to weight.

Table 3 reports the association between physical weight and marginal cost using an

[9]When estimating Equation 1, I also control for transport mode, which may be by air, sea, or land.

[10]Note that the unit in which quantity is measured is the same for all observation belonging to the same HS10 code and year. So, the supplier-product-year fixed effect is analogous to a supplier-product-unit type-year fixed effect.

OLS estimator. In the Colombia sample, a 10% increase in unit weight is associated with a 7.6% increase in marginal cost, with differences in physical weight explaining up to 70% of the within-firm price variation. Similar results apply to the US sample.

The OLS estimates, however, may be subject to an endogeneity concern. That is, unit weight, ω, may be correlated with other product characteristics that are themselves positively correlated with the marginal cost. For instance, cars featuring a wood interior trim are heavier, but they typically feature other quality-enhancing finishes that raise the marginal cost without raising the physical weight. The possible correlation between ω and ϵ, in such instances, will undermine the validity of the OLS estimator.

To address this concern, Table 3 also reports 2SLS estimates of the same regression. The IV employed in the 2SLS estimation utilizes the fact that each observation in the Colombia sample identifies the Colombian municipality by which import orders were placed. In a typical year, each municipality places multiple orders of the same HS10 product from various international suppliers. Considering this, I use the *lagged* physical weight of the municipality's imports from *other* suppliers to instrument for $\omega_{s,jkt}$.[11]

Table 3: Marginal cost across shipments from the same supplier (dependent: $\ln p$)

	Colombia		United States	
Regressor (log)	OLS	2SLS	OLS	2SLS
Unit weight, ω	0.760***	0.653***	0.731***	0.688***
	(0.0064)	(0.1087)	(0.0156)	(0.0236)
Within-R^2	0.68	...	0.60	...
First-Stage F-stat	...	3,010	...	1.1×10^5
Observations (rounded)	8,299,000		4,701,000	
Controls for transport mode	Yes		Yes	
Fixed Effects	firm×HS10×year		country×HS10×year	

Note: The independent variable is the unit f.o.b price, $\ln p_{s,jkt}$, and the estimating equation is Equation 1. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

Comparing the OLS and 2SLS results in Table 3, confirms the suspicion regarding a positive association between a firm's choice of output unit weight and its choice of other quality-enhancing product attributes. To elaborate, the results in Table 3 indicate that the OLS estimates are upward biased. This direction of bias implies a positive correlation between $\epsilon_{s,jkt}$ and $\omega_{s,jkt}$. Also, recall that $\epsilon_{s,jkt}$, among other things, accounts for the variation in intangible aspects of product quality (namely, φ). Considering this,

[11] In the case of the US data, I use the lagged physical weight of goods ordered by district s from other countries (excluding j) to instrument for $\omega_{s,jkt}$.

a firm's choice of φ seems to be positively correlated with its choice of ω. In Section 3, I present a theoretical model that clarifies this apparent link.

The validity of my instrument can be challenged if inventories clear out with a significant lag. In that case, markups may be sequentially correlated due to non-zero cross-period demand elasticities. To address this issue, I re-estimate Equation 1 using the 2$^{\text{nd}}$ and 3$^{\text{rd}}$ lags of the Colombian municipality's import unit weight from *other* suppliers. This choice of instrument shrinks the sample as I can construct the 2$^{\text{nd}}$ lag instrument for only post-2009 observations and the 3$^{\text{rd}}$ lag instrument for only post-2010 observations. The results are displayed in Table 4, and reinstate the original observation the marginal cost is increasing in unit weight.[12]

Table 4: Estimating Equation 1 with a more conservative IV

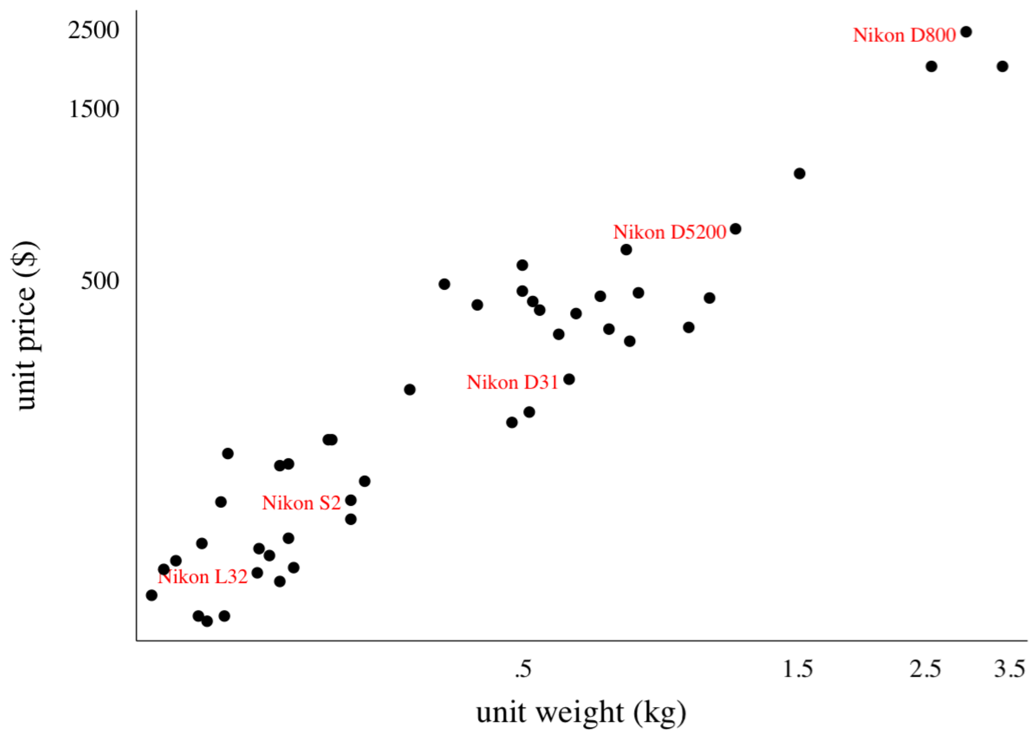
	2$^{\text{nd}}$ Lag IV		3$^{\text{rd}}$ Lag IV	
Regressor (log)	OLS	2SLS	OLS	2SLS
Unit weight, ω	0.772***	0.673***	0.779***	0.682***
	(0.0065)	(0.1203)	(0.0069)	(0.1125)
Within-R^2	0.69	...	0.70	...
First-Stage F-stat	...	1,878	...	1,130
Observations (rounded)	5,880,000		4,230,000	
Controls for transport mode	Yes		Yes	
Fixed Effects	firm$\times$HS10$\times$year		firm$\times$HS10$\times$year	

Note: The independent variable is the unit f.o.b price, ln $p_{s,jkt}$, and the estimating equation is Equation 1. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

Figure 1 sheds further light on Facts 1 and 2. It displays all the export shipments of *"Digital Cameras and Video Camera Recorders"* (code HS8525802000) from NIKON to the Colombian market in 2013. In-line with Fact 1, the unit weight of Nikon cameras varies considerably: the NIKON D31 weighs around 1 kg, while the NIKON D800 has a shipping weight of around 3 kgs. That is, the heaviest SLR camera supplied by NIKON in product code HS8525802000 is more than 3-times heavier than its lightest SLR model. Moreover, there is a strong association between unit price and unit weight. The heavier NIKON D800 is priced at $2,500, whereas the lighter NIKON D31 is priced only at $400. My analysis posits that, at least, part of this price difference is due to the heavier model being more costly to produce.

[12] To be clear, the marginal cost interpretation of these patterns holds insofar as markups are assumed to be uniform within firm$\times$product$\times$year cells. Or if, alternatively, the markup increases with unit weight but at a lower elasticity than the unit price, i.e., $\partial \ln \mu / \partial \ln \omega < \partial \ln p / \partial \ln \omega$.

Figure 1: Nikon camera shipments to Colombia in "HS8525802000"



Note: All observations pertain to year 2013 and concern exports of "Digital Cameras and Video Camera Recorders" belonging to HS10 code "HS8525802000" by Nikon.

Three outstanding concerns, though, remain with regards to the results reported in Table 3: (i) aggregation bias, (ii) measurement error, and (iii) non-monotonicity. To address the first concern, Appendix B.1 runs Regression 1 individually for each 6-digit HS6 industry (instead of pooling all products together). In the case of Colombia, the coefficient α is positive and exhibits a t-statistic that is greater than 2 for 1,741 (out of 1,772) HS6 industries. Coefficient α is negative and significant for only 29 HS6 industries, including "HS871190" (Motorcycles and Cycles) and "620719" (Men's Underwear). That is, Fact 2 is violated in only 29 out of 1,772 HS6 industries.

The concern with measurement error is that unit weight and unit price may be measured with error. The IV estimation can eliminate the bias due to measurement error provided that the instrument for ω (i.e., the lagged unit weight of the Colombian municipality's imports from other suppliers) is uncorrelated with measurement error in ω. Even then, however, there remains the concern that Q is used in calculating both the unit weight $\omega = W/Q$ and the unit price, $p = V/Q$, which can lead to a spurious correlation between ω and p. To rule out this possibility, Appendix B.2 directly regresses total value, $V_{s,jkt}$, on total weight, $W_{s,jkt}$, and total quantity, $Q_{s,jkt}$. The results indicate that, even after controlling for total quantity, total weight remains strongly and significantly correlated with the total value of goods in shipment s, jkt.

The concern with non-monotonicity is that some HS10 codes are broadly defined and encompass products with systematically different characteristics. In these cases, the results in Table 3 may be driven by unit weight absorbing the heterogeneity in other hidden product characteristics. To give an example, laptop computers with different screen sizes are usually lumped into the same HS10 category. In that case, the effect of unit weight on marginal cost may be driven entirely by screen size. Correspondingly, one may suspect that unit weight is negatively related to marginal cost if we were to control for screen size. To address this issue, I re-run Regression 1 on a sample that excludes 'Electronics' and 'Transport Equipments', for which HS10 codes are notorious for being broadly-defined. Table 14 of the appendix reports results concerning the trimmed sample. While encouraging these results cannot be pushed too much. The ideal robustness check would be to control for other tangible product characteristics (e.g., length, screen size, horse power), which are unfortunately not reported in the customs data.[13]

FACT 3. *The unit cost of transportation increases with unit weight more rapidly than the marginal cost of production, i.e.,* $\partial \ln \tau / \partial \ln \omega > \partial \ln mc / \partial \ln \omega$.

To establish this fact, I run the following regression that is a basic extension of the estimating equation in Hummels and Skiba (2004):

$$\ln \tau_{s,jkt} = \beta_{\omega} \cdot \ln \omega_{s,jkt} + \beta_{v} \cdot \ln v_{s,jkt} + \text{Controls}_{s,jkt} + \delta_{jkt} + \epsilon_{s,jkt}. \tag{2}$$

Recall that, in the above regression, $\tau \equiv T/Q$ denotes the unit transport cost, $\omega \equiv W/Q$ denotes the physical unit weight; and $v \equiv V/W$ denotes the value-to-weight ratio of the transported goods. The additional right-hand side variable, $\text{Controls}_{s,jkt}$, is composed of a set of controls for the mode of transportation (land, air, or sea) and shipment scale. Finally, δ_{jkt} controls for *supplier-product-year* fixed effects; and the idiosyncratic error terms, $\epsilon_{s,\omega ht}$, reflects measurement error plus non-systematic transport-cost-shifters that are specific to shipment s, jkt.

Before moving forward, let me briefly outline the connection between the above transport cost function and the one estimated in Hummels and Skiba (2004). To handle the fact that ω was not observable in their data, Hummels and Skiba (2004) assumed that $\omega_{s,jkt}$ is uniform within each fixed effect cell, i.e., $\omega_{s,jkt} = \omega_{jkt}$. Under this assumption, the variation in $\omega_{s,jkt}$ is entirely absorbed by the fixed effect, δ_{jkt}. As a result, $\beta_{\omega} \cdot \ln \omega_{s,jkt}$

[13] A large literature on hedonic price models estimates the effect of unit weight on prices, while controlling for other product characteristics. Most notably, Chwelos et al. (2008) find that heavier digital tablets exhibit a significantly higher price after we control for screen size, memory, ram, etc.; Fehder et al. (2009) find that heavier digital cameras exhibit a significantly higher price after we control for lens type, battery type, pixels, etc.; Chugh et al. (2011) find that heavier vehicles exhibit a significantly higher price after we control for engine size, fuel efficiency, transmission type, etc. In contrast to the aforementioned studies, Chwelos (2003) estimates that the unit weight of a laptop computer is negatively but insignificantly related to its price after we control for screen size, ram, memory, etc

drops out of the regression; and the transport cost function reduces to the specification estimated in Hummels and Skiba (2004). [14] However, following Fact 1, we know that this assumption is violated in the data; which is why $\omega_{s,jkt}$ is included as a covariate on the right-hand side of Equation 2.

As a first step, I estimate Equation 2 using an OLS estimator. The results, reported in Table 5, accord with Fact 3. The OLS estimates, however, may be biased due to the simultaneity between τ, ω, and v. The simultaneity may be driven by two distinct factors. On one hand, firms may be inclined to export lighter (low-ω) goods in response to higher transport costs. On the other hand, due to the classic "Washington Apples Effect," firms may also adjust the value-to-weight ratio of their exports in response to movements in transport costs.

Table 5: The determinants of unit transport cost (dependent: $\ln \tau$)

	Colombia		United States	
Regressor (log)	OLS	2SLS	OLS	2SLS
Value-to-weight, v	0.526***	0.419**	0.466***	0.377*
	(0.0145)	(0.1764)	(0.0214)	(0.229)
Unit weight, ω	1.037***	1.310***	0.959***	1.157***
	(0.0051)	(0.0575)	(0.0092)	(0.0923)
Within-R^2	0.74	...	0.59	...
First-Stage F-stat	...	1,109	...	291
Observations (rounded)	8,299,000		4,701,000	
controls for transport mode	Yes		Yes	
control for shipment scale	Yes		Yes	
fixed effects	firm×HS10×year		country×HS10×year	

Note: The independent variable is the unit transport cost, $\ln \tau_{s,jkt}$. The estimating equation is Equation 2. All standard errors are clustered by HS10 product. ***, **, and * respectively denote significance at the 1%, 5% and 10% levels.

Considering this issue, I re-estimate Equation 2 using a 2SLS estimator. The choice of instrument is inspired by Hummels and Skiba (2004), who instrument for v using

[14] To be more specific, Hummels and Skiba (2004) analyze the cross-national variation in transport costs and value-to-weight ratios within six-digit (HS6) industries for six countries. They observe the total weight (W) but not the total quantity (Q) per observation. So, instead, they assume that $\omega = W/Q$ is uniform within HS6 industry k, and estimate the following transport cost function (labeled "Equation 10" in their paper):

$$\ln \tau_{jit} = \beta_v \cdot \ln v_{jik} + \underbrace{\beta_W \cdot W_{jit} + \beta_D \cdot \text{Dist}_{ji}}_{\text{Controls}_{jkt}} + \delta_k + \epsilon_{jik},$$

where j indexes the exporting country and i indexes the importing country. They also use f (instead of τ) to denote the unit transport cost and p (instead of v) to denote the value-to-weight ratio.

lagged values. Given the richer structure of my data, I instrument for $\omega_{s,jkt}$ and $v_{s,jkt}$ with the lagged value of these variables on alternative routes. That is, for each shipment s, jkt to municipality m, I use the lagged unit weight and value-to-weight ratio of goods imported by municipality m from other suppliers (aside from j), to instrument for $\omega_{s,jkt}$ or $v_{s,jkt}$. The identifying assumption is that concurrent movements in transport costs are uncorrelated with the lagged unit weight and value-to-weight ratios of municipality m's *prior* imports from other suppliers.

Comparing the 2SLS and OLS results suggests that the instruments are operating in the expected direction. Presumably, an idiosyncratic increase in τ will prompt firms to export goods with (i) a lower unit weight (i.e., $cov(\omega, \epsilon) < 0$) and (ii) a higher value-to-weight ratio (i.e., $cov(v, \epsilon) > 0$), with the latter effect concerning the aforementioned "Washington Apples Effect." Considering this, the OLS estimate of β_ω should be attenuated, whereas the OLS estimate of β_v should exhibit an upward bias. Comparing the results reported in Table 5, indicates that the 2SLS estimator corrects these biases in the expected direction. Moreover, as noted in Appendix B.4, the results presented in Table 5 are robust to an alternative choice of instrument, which uses information on the export behavior of the Colombian firm placing import order, s, jkt.[15]

In summary, these results indicate that physical unit weight is a significant driver of the unit transport cost. Moreover, the unit transport cost increases more rapidly with unit weight than the marginal production cost: A 10% increase in unit weight increases the marginal cost of production by around 7% but increases the unit cost of transportation by around 13%. Encouragingly, the estimated coefficient on v under all specifications closely resembles the estimates of Hummels and Skiba (2004).

FACT 4. *The iceberg transport cost specification provides a semi-accurate "reduced-form" representation of τ's dependence on ω and v.*

Based on Fact 3, the unit transport cost is a function of the value-to-weight ratio and the unit weight of the transported goods, i.e., $\tau = \tau(\omega, v)$. Mainstream trade models, however, do not formally model either ω or v. Instead, they assume that transport costs are proportional to the f.o.b. unit price, i.e., $\tau(p) = \mathcal{T}p$. This reduced-form specification of transport costs is known as the "iceberg" assumption. Stated otherwise, Fact 4 asserts that $\tau(p) = \mathcal{T}p$ provides a semi-accurate reduced-form representation of the actual unit transport cost function, $\tau(\omega, v)$.

One way to cast the above claim is as a direct corollary of Facts 2 and 3. The iceberg assumption ($\tau = \mathcal{T}p$) can be otherwise stated as $\beta \equiv \partial \ln \tau / \partial \ln p = 1$.[16] Noting that

[15] This alternative instrument is motivated by the finding in Kugler and Verhoogen (2012) that Colombian firms which import higher-quality inputs tend to export higher-quality output.

[16] Several studies (e.g., Irarrazabal et al. (2015)) specify transport costs as having multiplicative and

$p = \omega v$, we can use the chain rule to express β as follows

$$\beta \equiv \frac{\partial \ln \tau}{\partial \ln p} = \frac{\partial \ln \tau}{\partial \ln \omega}\tilde{\alpha} + \frac{\partial \ln \tau}{\partial \ln v}\left(1 - \tilde{\alpha}\right),$$

where $\tilde{\alpha} \equiv \partial \ln \omega / \partial \ln p = 1 - \partial \ln v / \partial \ln p$. Fact 2 indicates that $\tilde{\alpha} > 0$; so β is essentially a weighted average of $\beta_\omega \equiv \partial \ln \tau / \partial \ln \omega$ and $\beta_v \equiv \partial \ln \tau / \partial \ln v$. Based on Fact 3, $\beta_\omega \approx 1.3$ and $\beta_v \approx 0.4$. So, together, these numbers imply that β should lie somewhere in between 0.4 and 1.3. To further narrow down this interval, we can crudely deduce from Fact 2 that $\tilde{\alpha}$ lies approximately in the 0.7 to 0.8 range, which implies that $\beta \approx 0.25 \times 0.4 + 0.75 \times 1.3 \approx 1.075$.[17]

A formal estimate of β can also be attained by performing the following estimation:

$$\ln \tau_{s,jkt} = \beta \cdot \ln p_{s,jkt} + \text{Controls}_{s,jkt} + \delta_{jkt} + \epsilon_{s,jkt}, \tag{3}$$

where, as before, δ_{jkt} controls for *supplier-product-year* fixed effects, and $\text{Controls}_{s,jkt}$ is composed of a set of controls for mode of transportation and scale effects. I first estimate the above regression using an OLS estimator. But since both components of p (namely, value-to-weight, v, and unit weight, ω) may be correlated with $\epsilon_{s,jkt}$, I also conduct a 2SLS estimation of the same equation.[18]

The estimation results reported in Table 6 indicate that the estimated elasticity, β, is close to 1 under all specifications. In other words, transport costs are not of the exact "iceberg" type, but are "quasi-iceberg." Here, the difference between the OLS and 2SLS estimates are not as pronounced. This outcome is perhaps expected given that the two components of $p = v.\omega$ are correlated with the error term, ϵ, in different directions. More specifically, $cov(v, \epsilon) > 0$ due to the "Washington Apples Effect," whereas $cov(\omega, \epsilon) < 0$. As a result, the direction of the OLS bias is ambiguous and the extent of the bias can be potentially small.

The finding that transport costs exhibit a *quasi-iceberg* specification should be interpreted with caution. First, my analysis is only focusing on discrete goods, which typically belong to the "Transport Equipment," "Electronics & Appliances," and "Machinery" sectors. In non-discrete industries, like "Food," "Chemicals," or "Textile & Apparel," the unit weight of goods is by construction constant and equal to *one*. Correspondingly, for these goods, β_ω does not contribute to the iceberg elasticity, β. So, if one were to estimate

additive components: $\tau = \mathcal{T}p + t$. Under this specification, $\beta \equiv \partial \ln \tau / \partial \ln p$ identifies the share of the multiplicative component: $\beta = \mathcal{T}p / (\mathcal{T}p + t)$.

[17]We can easily relate the above argument to the Hummels and Skiba (2004) estimation. Their assumption that unit weight is uniform within fixed effect cells, corresponds to a value of $\tilde{\alpha} = 1$, which in turn implies that $\beta \approx 0.4$.

[18]Similar to before, I use the lagged unit price of the importing municipality's orders from other suppliers to instrument for $p_{s,jkt}$.

Table 6: Testing the Iceberg Cost Specification (dependent: $\ln \tau$)

	Colombia		United States	
Regressor (log)	OLS	2SLS	OLS	2SLS
Unit price, $p = v \times \omega$	0.935***	1.085***	0.874***	0.957***
	(0.0077)	(0.0257)	(0.0105)	(0.0402)
Within-R^2	0.69	...	0.53	...
First-Stage F-stat	...	2.9×10^4	...	2.3×10^4
Observations	8,299,000		4,701,000	
controls for transport mode	Yes		Yes	
control for shipment scale	Yes		Yes	
fixed effects	firm×HS10×year		country×HS10×year	

Note: The independent variable is the unit transport cost, $\ln \tau_{s,jkt}$, and the estimating equation is Equation 3. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

β for non-discrete goods, the estimated value would be considerably lower—see Section 5 for formal estimates. This concern notwithstanding, my analysis applies to only transport costs, which are one of the many components of international trade costs. Considering this, the approach in Irarrazabal et al. (2015) would be more appropriate when evaluating the iceberg cost assumption as a whole.

Fact 5. *Heavier varieties of the same product exhibit greater product appeal or quality, with unit weight explaining around 60% of the cross-supplier variation in product appeal.*

As noted in the Introduction, the above fact aligns with an extensive body of research on consumer psychology (Jostmann et al. (2009); Lindstrom (2006); Piqueras-Fiszman et al. (2011); Piqueras-Fiszman and Spence (2012)). To document it here, I first need to estimate the quality of the traded goods in my sample. To do so, I follow the approach popularized by Khandelwal (2010), which involves estimating an import demand function and computing quality as the excess demand conditional on price. Identifying the demand function, however, requires plausibly exogenous cost-shifters. Given the state-of-the-art in the literature, I can only estimate the demand parameters and product quality at the *supplier-product-year* level. Accordingly, I collapse the original samples, so that each observation represents a *supplier×HS10 product×year* (jkt). I then estimate the following constant elasticity demand function,

$$\ln q_{jkt} = \varepsilon_k \cdot \ln \tilde{p}_{jkt} + \beta_k X_{jkt} + \varphi_{jk} + \tilde{\varphi}_{jkt},$$

where $\tilde{p}_{jik}$ denotes the consumer price, which is the f.o.b. price plus transportation costs and tariffs; $\beta_k X_{jkt}$ controls for possible patterns of cross-substitutability, which I will elaborate on shortly; and the *supplier-product* fixed effect plus the residual ($\varphi_{jkt} \equiv \varphi_{jk} + \tilde{\varphi}_{jkt}$) can be interpreted as quality plus measurement error.

To estimate the above demand function with firm-level data, I borrow the approach from Lashkaripour and Lugovskyy (2018). That is, I interact the monthly composition of lagged firm-level exports with concurrent aggregate movements in the monthly exchange rate to construct a firm-level measure of exposure to exchange rate shocks. I use this shift-share instrument to estimate a firm-level import demand function, with $\beta_k X_{jkt}$ controlling for the possibility that the cross-national and sub-national elasticities of substitution differ. Appendix C provides a thorough description of the firm-level demand estimation borrowed from Lashkaripour and Lugovskyy (2018).

In the case of the US data, I lack firm-level information to construct the previously-described shift-share instrument. Instead, I borrow the approach proposed by Khandelwal (2010), which is to instrument for $\tilde{p}_{jkt}$ with the tariff rate and utilize the cross-national variation in sales to identify the demand elasticity ε_k. In this case, $\beta_k X_{jkt}$ controls for the possibility that the cross-industry and sub-industry elasticities of substitution differ. Appendix C also provides a thorough description of the country-level demand estimation borrowed from Khandelwal (2010).

Once the demand function is estimated, we can infer the quality of supplier j in product category k in year t as follows:

$$\hat{\varphi}_{jkt} = \ln q_{jkt} - \hat{\varepsilon}_k \cdot \ln \tilde{p}_{jkt} - \hat{\beta}_k X_{jkt}$$

In the case of Colombia, the demand estimation identifies the quality level for (about) 1,346,000 firm-product-year combinations. In the case of the US, the demand estimation identifies the quality level for (about) 1,927,000 country-product-year combinations. Using these quality estimates, I then run the following regression to study the association between unit weight and product quality:[19]

$$\hat{\varphi}_{jkt} = b_\omega \ln \omega_{jkt} + b_v \ln v_{jkt} + \delta_{kt} + \epsilon_{jkt}. \tag{4}$$

The inclusion of the value-to-weight ratio, v, as an additional covariate is motivated by the fact that quality may increase with intangible attributes like design or marketing that operate orthogonally to physical weight.

The estimation results displayed in Table 7 indicate that both the physical unit weight

[19] In Equation 4, ϵ_{jkt} accounts for idiosyncratic taste and measurement error. Under the taste interpretation, the identifying assumption is that ω and ν are chosen by firms prior to the realization of ϵ_{jkt}. A similar assumption is made in the discrete choice trade literature, whereby entry/exit choices are made prior the realization of idiosyncratic taste shifters (Khandelwal (2010)).

and the value-to-weight ratio explain nearly 90% of the across-supplier variation in quality. The elasticity of quality w.r.t. to both variables is also similar at around 2-2.5. The Shapley decomposition of the R-squared is, however, more revealing. In the Colombia sample, around 53% of the cross-firm variation in product appeal/quality is driven by differences in output unit weight, with only 34% explained by differences in output value-to-weight ratio. In the US sample, around 63% of the cross-national variation in product quality is driven by differences in unit weight, with only 27% of the variation explained by differences in the value-to-weight ratio of the exported goods.

Table 7: The Determinants of Product Quality

	Colombia		United States	
Regressor (log)	coefficient	Shapley $\%R^2$	coefficient	Shapley $\%R^2$
Unit Weight, ω	2.426***	60.5%	2.152***	70.4%
	(0.0010)		(0.0005)	
Value-to-weight, v	2.183***	39.5%	1.956***	29.6%
	(0.0011)		(0.0007)	
Overall R^2	0.87		0.89	
Observations (rounded)	1,347,000		1,927,000	
Level of quality estimation	firm-product-year		country-product-year	
regression fixed effect	HS10$\times$year		HS10$\times$year	

Note: The independent variable is the output quality, ϕ_{jkt}, and the estimating equation is Equation 4—see Appendix C for a description of the quality estimation. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

Table 17, in the appendix, reports the association between product weight and quality for individual industries. There is great cross-industry heterogeneity in this regard. For 'Textile and Apparel', unit weight can explain only 24% of the variation in output quality based on the Shapley R-squared decomposition. For 'Furniture and Wood Products', by comparison, unit weight can explain 72% of the variation in output quality.

2.2 Discussion: *Within Firm×Product Markup Heterogeneity*

When documenting Fact 2, I assumed that markups are uniform within *firm×HS10 product×year* cells. This assumption can be suspect in certain product categories like those concerning autos, where multiple types of cars are lumped together into one HS10 category. There is also evidence that firms charge a higher markup on higher quality varieties of the same product (Piveteau and Smagghue (2019)). So, to the extent that weight heterogeneity reflects quality heterogeneity, one may suspect that heavier varieties of the same product feature a higher markup.

Unfortunately, controlling for markup heterogeneity within *firm*×*HS10 product*×*year* cells is infeasible with existing estimation techniques. To control for markup heterogeneity using the cost-side approach in De Loecker and Warzynski (2012), I need data on input shares for individual varieties belonging to the same *firm*×*HS10 product*×*year* cell. To control for markup heterogeneity using the demand-side approach, I need to estimate a demand elasticity for each individual variety within a *firm*×*HS10 product*×*year* cell. To do so, I need to identify a plausibly exogenous cost shifter that varies across varieties supplied by the same firm, in the same product category, in the same year. The structure of my data does not permit either of these approaches.

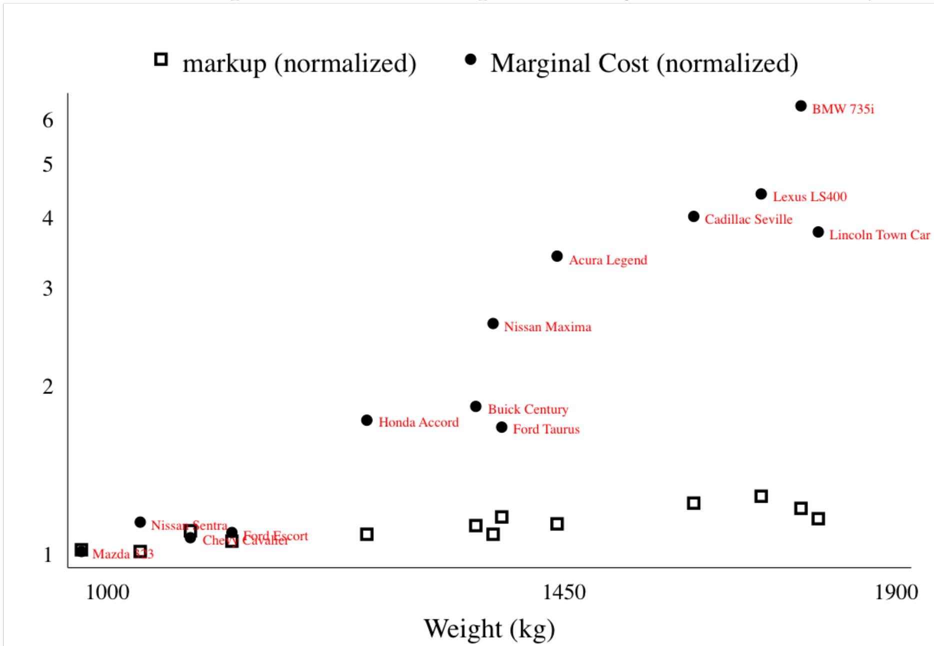
To address the above concern, I instead turn to the estimates in Berry et al. (1995). They estimate the markup for various models of cars sold in the U.S. market during the 1979-1990 period. Most of the models included in their analysis can be classified under HS code, "HS8703239000". This is one of the most suspect product codes as far as my assumption on uniform markups is concerned. Using the estimates reported by Berry et al. (1995), we can decompose the price of each model of car, i, into a markup and a marginal cost component: $p_i = \mu_i \times mc_i$.[20]

Figure 2 plots the markup (μ_i) and the marginal cost (mc_i) for each model of car in Berry et al. (1995) against its unit weight (ω_i). The markup clearly increases with unit weight but with a significantly lower elasticity than the marginal cost, i.e., $\partial \ln mc / \partial \ln \omega > \partial \ln \mu / \partial \ln \omega$. The elasticity of markup with respect to unit weight is $\partial \ln \mu / \partial \ln \omega = 0.1$ with an $R^2 = 0.74$. The elasticity of marginal cost with respect to unit weight, by comparison, is $\partial \ln mc / \partial \ln \omega = 2.9$ with an $R^2 = 0.90$.

Presumably, within *firm*×*HS10 product*×*year* cells, the elasticity of markup with respect to unit weight, $\partial \ln \mu / \partial \ln w$, is less than 0.1, since (i) the dataset in Berry et al. (1995) spans multiple firms, and (ii) HS10 codes in the auto industry are notorious for being broadly-defined. But even if we suppose that $\partial \ln \mu / \partial \ln w = 0.1$, then Facts 2 and 3 can still be stated as is. Based on the analysis following Fact 2, $\partial \ln \mu / \partial \ln w + \partial \ln mc / \partial \ln w = 0.7$, which implies that $\partial \ln mc / \partial \ln w = 0.6$ if $\partial \ln \mu / \partial \ln w = 0.1$. Fact 3 is also reinforced as there is now an even bigger wedge between the elasticity at which the transport cost increases with unit weight and the elasticity at which the marginal production cost increases with unit weight.

[20] The marginal cost in the above decomposition may also include transport costs. Based on Fact 4, transport costs are quasi-iceberg. So, the marginal cost can be decomposed into a multiplicative transport cost shifter, $\mathcal{T}_i$, and a pure production cost component, $\tilde{mc}_i$: $mc_i = \mathcal{T}_i \times \tilde{mc}_i$. By construction, $\partial \ln \mathcal{T} / \partial \ln \omega = 0$, which implies that $\partial \ln mc / \partial \ln \omega = \partial \ln \tilde{mc} / \partial \ln \omega$.

Figure 2: The relationship between markup and weight based on Berry et al. (1995)



Note: Price and markup values are relative to the price and markup of Mazda 323. Data for markup and price, which implicitly imply the marginal cost, are taken directly from Table 8 in Berry et al. (1995).

3 Modeling Firm's Choice of Output Weight

In light of Facts 1-5, I develop a simple, partial equilibrium framework to study the firms' choice of output unit weight. One can alternatively perceive the following framework as one that indirectly models the firms' choice of raw inputs. To be more specific, the firms' choice regarding the quantity and type of raw inputs uniquely pins down the unit weight of its output, ω, and also influences its output quality, φ. So, given the one-to-one correspondence between raw input usage and ω, we can simply model the firm's input choice indirectly from the point of ω.

One of the main elements of the present model is motivated by Fact 5. I assume that product quality is determined by two distinct margins:

1. ***Physical unit weight*** (ω) which reflects the extent to which raw inputs are used in the production of a good; and
2. ***Intangible product appeal*** (ν) which concerns features like product design or marketing.

Considering this, I specify product quality, φ, as a function of ω and ν as follows:

$$\varphi_i\left(\omega,\nu\right) = \left(A_i\omega^{\gamma} + B_i\nu^{\gamma}\right)^{\frac{1}{\gamma}}. \tag{5}$$

In addition to beings increasing in both arguments, the above formulation admits substitutability between ν and ω. Here, the subscript i indexes the destination market, and accounts for the possibility that different markets value ω and ν differently. It is important to note that the CES formulation is not consequential to the theoretical results that follow. What actually matters, instead, is that $\varphi_i(\varphi, \omega)$ be homogeneous of degree one and increasing in both arguments.

Demand. Each firm serving market i faces the following Marshallian demand function

$$q = \varphi_i(\omega, \nu) \mathcal{D}_i(\tilde{p}, y_i).$$

That is, the demand facing a firm is a function of its output price inclusive of transport costs, $\tilde{p}$, the representative consumer's income, y_i, and the quality of the firm's output, $\varphi_i(\omega, \nu)$. I assume that the demand function is well-behaved, in that it exhibits a sufficiently negative price elasticity $\partial \ln \mathcal{D}_i / \partial \ln \tilde{p} < -1$ and a positive income elasticity, $\partial \ln \mathcal{D}_i / \partial \ln y_i > 0$.

Supply. Production and delivery employs labor from the firm's country of origin. Specifically, a firm located in country ℓ faces the following linear marginal cost of production,

$$\mathcal{C}_\ell(\omega, \nu, z, w_j) = c_\ell(\omega, \nu) w_\ell / z,$$

which is increasing in the local wage rate w_ℓ, the output unit weight ω (i.e., $\partial c_\ell(.) \partial \omega > 0$), and intangible product appeal ν (i.e., $\partial c_\ell(.) \partial \nu > 0$); but is decreasing in the firm-level productivity, z. The fact the $c_\ell(.,.)$ is a country ℓ-specific function accounts for the possibility of comparative cost advantage in the intangible margin of quality, ν.

Transportation employs labor from both the origin country (ℓ) and the destination country (i), with the unit cost of transportation between countries ℓ and i given by

$$\tau(\omega, \nu, w_\ell, w_i; d_{\ell i}) = \mathcal{T}(\omega, \nu, z; d_{\ell i}) w_i^\eta w_\ell^{1-\eta}.$$

In the above expression $d_{\ell i}$ denotes geographical distance and other barriers that impede the flow of goods from country ℓ to i. The dependence of transport costs on ω, ν, and z is motivated by Fact 3. The inclusion of ω follows directly from the verbal description of Fact 3, but let me elaborate on the inclusion of ν and z. Both ν and z influence the value-to-weight ratio of the traded goods without influencing the unit weight, ω. That is, $v = v(\nu, z, ...)$. So, the fact that $\tau(.)$ is a direct function of $v(\nu, z, ...)$ (per Fact 3), indicates that it is also by construction a function of both ν and z.

I do not explicitly model the determination of ν and z as an outcome of firm's choice. Instead, as is standard in the literature, I assume that firms in country ℓ draw ν and z from distributions $H_\ell(\nu)$ and $F_\ell(z)$. I assume that there is zero cross-cost passthrough between goods sold by a firm in different markets. As a result, firm $\jmath$ located in country

ℓ sets the price and unit weight of the goods sold to market i by solving the following *market-specific* profit maximization problem:

$$\max_{\omega,\tilde{p}} \quad \left(\tilde{p} - \left[c_\ell\left(\omega,\nu_J\right)w_\ell/z_J + \tau\left(\omega,\nu_J,z_J;d_{\ell i}\right)w_i^\eta w_\ell^{1-\eta}\right]\right)\varphi_i\left(\omega,\nu_J\right)\mathcal{D}_i\left(\tilde{p},y_i\right).$$

The above expression clearly outlines the trade-offs faced by firm J. On one hand, increasing the unit weight of output enhances the product appeal and increases sales through $\varphi_i\left(\omega,\nu_J\right)$. On the other hand, increasing the unit weight of output (i) increases the cost of production through the term $c_\ell\left(.\right)$, as heavier output requires more raw inputs; and also (ii) increases the cost of transportation through the term $\tau\left(.\right)$. Correspondingly, the first order condition characterizing firm J's optimal choice of output unit weight in market i is given by

$$\rho_{Ji}\epsilon_\tau + \left(1-\rho_{Ji}\right)\epsilon_c = \epsilon_\varphi,$$

where $\rho_{Ji} = \tau_{Ji}/\tilde{p}_{Ji}$ denotes the share of transports costs in the firm's final price, with $\tau_{Ji} = \tau\left(\omega_{Ji},\nu_J,w_\ell,w_i;d_{\ell i}\right)$. $\epsilon_\tau \equiv \partial\ln\tau/\partial\ln\omega$ denotes the elasticity of unit transport cost *w.r.t.* unit weight, $\epsilon_c \equiv \partial\ln c/\partial\ln\omega$ denotes the elasticity of marginal cost *w.r.t.* unit weight; and $\epsilon_\varphi \equiv \partial\ln\varphi/\partial\ln\omega$. Differentiating Equation 5 implies that $\epsilon_\varphi = A_i\omega^\gamma/\left(A_i\omega^\gamma + B_i\nu^\gamma\right)$. So, the above optimality condition yields an optimal unit weight equal to

$$\omega_{Ji}^* = \tilde{A}_i\left(\frac{1}{\rho_{Ji}\epsilon_\tau + \left(1-\rho_{Ji}\right)\epsilon_c} - 1\right)^{\frac{1}{\gamma}}\nu_J, \tag{6}$$

where $\tilde{A}_i \equiv \left(A_i/B_i\right)^{1/\gamma}$ is a market-level shifter. Based on Facts 2 and 3,[21]

$$\epsilon_\tau > \epsilon_c,$$

which immediately indicates that ω_{Ji}^* is lower for high-ρ firms. That is, firms for which a higher fraction of the final price is driven by transport costs tend to sell lighter output. To push this result further, we can apply the Implicit Function Theorem to Equation 6, noting that $\rho_{Ji} = \rho\left(\omega_{Ji},\nu_J,w_\ell,w_i,z_J;d_{\ell i}\right)$. Doing so and considering that $\partial\rho\left(.\right)/\partial\omega_{Ji} > 0$, $\partial\rho\left(.\right)/\partial d_{\ell i} > 0$, and $\epsilon_\tau > \epsilon_c$, we can conclude that distance decreases the optimal unit weight of exported goods. In particular,

$$\partial\omega_{Ji}^*/\partial d_{\ell i} < 0, \quad J \in \mathcal{J}_\ell \tag{7}$$

where recall that $d_{\ell i}$ is the distance for country ℓ to market i, with $\mathcal{J}_\ell$ denoting the

[21]Note that ϵ_τ corresponds to the estimated coefficient β_τ, while ϵ_ω corresponds to the estimated coefficient α. Based on the estimation results presented in Section 2, $\epsilon_\tau \approx 1.3$ and $\epsilon_\omega \approx 0.7$.

set of all firms serving market i from country ℓ. Likewise, a higher wage rate in the origin country influences the choice of ω through its effect on ρ_{ji}. To elaborate, note that transportation combines labor from both the origin and the destination countries, whereas production only employs labor in the origin country. That being the case, an increase in w_ℓ raises the marginal cost of production disproportionally more than the marginal cost of transportation. These asymmetric effects entail that $\partial\rho(.)/\partial w_\ell < 0$ for all $j \in \mathcal{J}_{\ell i}$. This outcome combined with $\epsilon_\tau > \epsilon_c$, indicates that (all else the same) a higher wage in the local economy induces firms to export heavier goods,[22]

$$\partial\omega^*_{ji}/\partial w_\ell > 0, \quad j \in \mathcal{J}_{\ell i}. \tag{8}$$

Together, Expressions 7 and 8 suggest that in a cross-section of countries, exports from advanced economies should exhibit a higher unit weight, whereas exports from distant economies should exhibit a lower unit weight. Moreover, to the extent that unit weight determines product quality, these outcomes are reflective of quality specialization along the weight margin.

The claim preceding Expression 8, however, requires further elaboration, as wages are determined endogenously in the general equilibrium. To be specific, the wage rate in country ℓ is determined primarily by the exogenously-assumed distributions, $F_\ell(z)$ and $H_\ell(\nu)$, plus the country's transportation efficiency and geo-location. A better productivity-distribution, $F_\ell(z)$, increases the wage rate, but also imposes downward pressure on output prices. A better intangible quality-distribution, $H_\ell(\nu)$, imposes upward pressure on both wages and prices. Likewise, a better transportation technology also exerts upward pressure on wages. So, for the argument preceding Expression 8 to hold in a general equilibrium setup, we need the combination of these forces to imply the following: $\partial \ln p_{ji}/\partial \ln w_\ell > \partial \ln \tau_{ji}/\partial \ln w_\ell$ for all $j \in \mathcal{J}_\ell$. This outcome is exactly what we observe in the data based on the estimates in Limao and Venables (2001), Schott (2004), and Hummels and Klenow (2005).[23]

Finally, Equation 6 implicitly highlights another channel through which advanced economies are prompted to specialize in heavier goods. Based on the equation, a firm's choice of output unit weight increases proportionally with its intangible product appeal, ν. Recall that this relationship was also confirmed by the data analysis presented in Section 2.[24] Hence, provided that the distribution of intangible product quality ($H_\ell(\nu)$)

[22] More formally, the above result derives from applying the Implicit Function Theorem to Equation 6, while noting that $\partial\rho(.)/\partial w_\ell < 0$, $\partial\rho(.)/\partial\omega_{ji} > 0$, and $\epsilon_\tau > \epsilon_c$.

[23] To be more specific, Schott (2004) and Hummels and Klenow (2005) document that $\partial \ln p_{ji}/\partial \ln w_\ell > 0$ for all $j \in \mathcal{J}_\ell$, whereas Limao and Venables (2001) document that $\partial \ln \tau_{ji}/\partial \ln w_\ell < 0$ for all $j \in \mathcal{J}_\ell$.

[24] More specifically, recall that comparing the OLS and 2SLS estimates of Equation 1 implied that non-weight-related costs shifters (which includes ν) are positively correlated with the choice of unit weight.

is stochastically dominant in advanced economies, they would on average supply heavier output. This channel, however unlike the previous channel, is partly driven by the functional-form assumption on $\varphi(\omega, \nu)$. The above arguments are summarized in the following proposition.

Proposition. [***Weight-Based Quality Specialization***] (i) *Advanced economies specialize in heavier (high-ω) varieties; while* (ii) *Geographically distant suppliers specialize in lighter (low-ω) varieties of the same good.*

To complement the above proposition, a discussion regarding the other dimension of product quality, ν, is in order. Unlike unit weight, intangible product appeal, ν, is not directly observable but can be inferred from value-to-weight ratios with some noise. In particular, the value-to-weight ratio of goods exported by firm $\jmath \in \mathcal{J}_{\ell i}$ can be expressed as a function of its intangible product appeal, $\nu_\jmath$, its productivity, $z_\jmath$, the underlying demand elasticity, $\varepsilon_{\jmath i}$ (which determines the optimal markup), plus country-level statistics like labor wage, w_ℓ, and geo-distance to market i, $d_{\ell i}$. Namely,

$$v_{\jmath i} = v\left(\nu_\jmath, z_\jmath \varepsilon_{\jmath i}; w_\ell, d_{\ell i}\right).$$

Here, given the focus of the paper, I did not formally model the determination of $\nu_\jmath$. Instead, I simply assumed that $\nu_\jmath$ is drawn from a country-level distribution. An immense body of theory has been devoted to internalizing the link between the level of economic development and the distribution of $\nu_\jmath$. The general premise of these theories is that exports from high-wage economies exhibit (on average) a higher ν, either due to their quality-biased factor endowment (Schott (2004)) or their greater home-market demand for quality (Fajgelbaum et al. (2011)). So, at least from the point of these theories, we would expect a positive relationship between the income per capita of the exporting economy and the value-to-weight ratio of exports, i.e., $\partial v_{\jmath i}(.)/\partial w_\ell > 0$ for all $\jmath \in \mathcal{J}_{\ell i}$.

Relatedly, the effect of distance, $d_{\ell i}$, on the value-to-weight ratio of country-level exports (defined as $\bar{v}_{\ell i} = \sum_{\jmath \in \mathcal{J}_\ell} q_{\jmath i} v_{\jmath i} / \sum_{\jmath \in \mathcal{J}_\ell} q_{\jmath i}$) is governed by two countervailing forces. On one hand, due to the "Washington Apples Effect," high-ν firms have a relative cost advantage in distant markets. Since $\partial v_{\jmath i}/\partial \nu_\jmath > 0$, the aforementioned effect can lead to a positive relationship between $d_{\ell i}$ and $\bar{v}_{\ell i}$. On the other hand, high-productivity (high-z) firms are more likely to sort into distant markets à la Melitz (2003). Given that $\partial v_{\jmath i}/\partial z_\jmath < 0$, this latter effect can lead to a negative relationship between $d_{\ell i}$ and $\bar{v}_{\ell i}$. Based on existing evidence, it appears that the former effect generally dominates the latter.[25] In the next section, I formally test these predictions using data on export unit

[25]There is also the quality-sorting channel that operates similar to productivity-sorting but in the opposite direction—see Baldwin and Harrigan (2011) and Crozet et al. (2012).

weights and value-to-weight ratios.

Finally, my simple model overlooks the extensive margin of trade, but weight-based quality specialization may alternatively arise from firm-selection. To make this point, consider the following variation of Baldwin and Harrigan's (2011) adaptation of Melitz (2003): A large pool of *ex ante* identical firms draw their output unit weight, ω, from an exogenously-assumed distribution. Also, firms have to incur a fixed cost to penetrate individual markets. Following the same line of arguments in Baldwin and Harrigan (2011), firms with a lower output weight will sort in distant markets provided that the elasticity of output quality *w.r.t.* to unit weight is sufficiently low:

$$\epsilon_\varphi < (1-\varepsilon)\left(\epsilon_\tau + \epsilon_c\right),$$

where ε denotes the constant elasticity of demand facing individual firms.[26] Based on the demand estimation reported results in Table 16 of the appendix, $\varepsilon \approx -2.3$. We can, thus, verify that the above condition holds using on the estimation results from Section 2, which suggest that $\epsilon_\varphi \approx 2.5$, $\epsilon_\tau \approx 1.3$, and $\epsilon_c \approx 0.65$. That being the case, both firm-selection and the optimal choice of output weight by firms contribute to *weight-based quality specialization*.

4 Evidence on Weight-Based Quality Specialization

This section formally tests the prediction that –at the country-level– the unit weight of exports is (ii) negatively correlated with geo-distance, and (ii) positively correlated with the GDP per worker of the exporting economy. To test these two predictions, I use the same data described in Section 2. Recall that the data from Colombia reports import statistics at the *shipment*×*firm*×*product*×*year* level, while the data from the US reports trade statistics at the *district*×*country*×*product*×*year* level. The predictions of the model, however, concern the variation in trade statistics based on group-level (country-level) characteristics such as geo-distance and GDP per worker.

Hence, to conduct my analysis, I group all observations pertaining to the same *country-product-year* cell together. Doing so leaves me with around 275,000 observations in the Colombia sample and 1,970,000 observations in the US sample. For each observation jkt, corresponding to *exporting country* j×*HS10 product* k×*year* t, I can calculate the average unit weight ω_{jkt}, the value-to-weight ratio, v_{jkt}, and the unit f.o.b. price, p_{jkt}. I combine this information with matching data on distance, GDP per capita, total GDP, and regional trade agreements in year t from Head et al. (2010).

[26]The assumption here is that demand has a CES parameterization à la Melitz (2003).

I then run the following regression for each of the variables $y_{jkt} = \bar{\omega}_{jkt}$, $\bar{v}_{jkt}$, and $\bar{p}_{jkt}$,

$$\ln y_{jkt} = b_1 \ln \text{Dist}_j + b_2 \ln \text{GDP p/c}_{jt} + Controls_{jt} + \delta_{kt} + \epsilon_{jkt}, \tag{9}$$

where Dist_j denotes the geo-distance between country j and either Colombia or the US; GDP p/c_{jt} denotes the GDP per worker of country j in year t; $Controls_{jt}$ corresponds to a set of additional controls for market size, remoteness, trade agreements, and mode of transportation; and δ_{kt} controls for product-year fixed effects. While Equation 9 includes an extensive set of country-level controls, there is a concern that it still omits hidden country-specific covariates that influence export composition. In light of this concern, I also use the following specification that is more conservative and includes product×country and year fixed effects:

$$\ln y_{jkt} = b \ln \text{GDP p/c}_{jt} + Controls_{jt} + \delta_{jk} + \delta_t + \epsilon_{jkt}. \tag{10}$$

The above specification, though, can only identify the effect GDP per capita on export composition, as distance effects are absorbed by the country×product fixed effect, δ_{kt}.

The estimation results are reported in Table 8, indicating that (a) economies far away from the US or Colombia export systematically lighter goods to these markets, while (b) advanced economies (that have a high GDP per worker) export heavier goods. To the extent that heavier goods are of higher quality, these findings confirm my earlier proposition about *weight-based* quality specialization.

Next, I am interested in how weight-based quality specialization interacts with the other margin of quality specialization, which concerns *intangible* product appeal (ν). As noted earlier, this latter margin has been the primary focus of prior theories, like Schott (2004), Fajgelbaum et al. (2011), and Feenstra and Romalis (2014). The results in Table 8 indicate that a higher GDP per capita is associated with a significantly higher export value-to-weight ratio. So, to the extent that value-to-weight ratios reflect intangible product appeal, weight-based quality specialization reinforces the other margin of quality specialization in the case of advanced economies.

Distance has a positive effect on the export value-to-weight ratio, which is presumably due to the "Washington Apples Effect." So, to the extent that value-to-weight ratios reflect intangible product appeal, the *Washington-Apples*-driven quality specialization countervails weight-based quality specialization in the case of distant economies. As a result, the effect of distance on the export unit price ($p = \omega v$) is ambiguous. On one hand, geo-distance induces firms to decrease the unit weight of their exports, ω. On the other hand, it induces them to increases the value-to-weight ratio of their exports, v, by upgrading their intangible product appeal. The overall effect of distance on p, therefore, depends on the relative magnitude of these countervailing effects. In the

Table 8: The Cross-national Variation in Export Unit Weights and Value/Weight Ratios

	Colombia		United States	
	ln GDP p/c	ln Dist	ln GDP p/c	ln Dist
	Dependent variable: **unit weight**			
Equation 9	0.126***	−0.147***	0.058***	−0.136***
	(0.029)	(0.036)	(0.007)	(0.016)
Equation 10	0.684*	...	0.028	...
	(0.405)		(0.076)	
	Dependent variable: **value-to-weight**			
Equation 9	0.218***	0.132***	0.184***	0.065***
	(0.023)	(0.033)	(0.007)	(0.014)
Equation 10	0.443	...	0.349***	...
	(0.292)		(0.082)	
	Dependent variable: **unit price**			
Equation 9	0.344***	−0.013	0.242***	−0.071
	(0.050)	(0.065)	(0.012)	(0.021)
Equation 10	1.127**	...	0.377***	...
	(0.503)		(0.067)	
Observations (rounded)	275,000		1,970,000	
GDP Control	YES		YES	
Transport mode Control	YES		YES	
FTA Control	YES		YES	
Remoteness Control	YES		YES	
Tariff Control	YES		YES	

Note: The estimating equations are Equations 9 and 10. Equation 9 features product-year fixed effects. Equation 10 features country-product fixed effects and year dummies. All standard errors are clustered by country of origin and year. *** denotes significance at the 1% level; ** denotes significance at the 5% level; and * denotes significance at the 10% level.

Colombia and US samples, neither effect seems to dominate.

4.1 Evidence Based on Changes in Export Unit Weight

In the spirit of Schott (2004), I present additional evidence for weight-based quality specialization using the longitudinal change in export composition. To this end, I estimate the change in export unit weights and value-to-weight ratios as a function of the change in the exporter's GDP per capita and oil price-adjusted distance.[27] I use a long difference estimator for this purpose, which operates as follows: Consider two multi-year periods, A and B. For each period and each variable x, I construct period-specific averages as $\bar{x}_A \equiv \frac{1}{n}\sum_{t\in A} x_t$, and $\bar{x}_B \equiv \frac{1}{n}\sum_{t\in B} x_t$, with n denoting the number of years in each period. I then calculate the long difference associated with each variable x as $\Delta x = \bar{x}_B - \bar{x}_A$. I finally estimate the following equation, where $y_{jkt} = \bar{\omega}_{jkt}$, $\bar{v}_{jkt}$, and $\bar{p}_{jkt}$:

$$\Delta \ln y_{jk} = b_1 \Delta \ln(\text{Dist}_j \times P_{\text{oil}}) + b_2 \ln \Delta \text{GDP p/c}_j + Controls_j + \delta_k + \epsilon_{jk}. \qquad (11)$$

In the above estimating equation, δ_k controls for HS10 product fixed effects, $\text{Dist}_j \times P_{\text{oil}}$ denotes distance times the global price of oil in that period; and $Controls_{jt}$ accounts for changes in market size, trade agreement status, and average mode of transportation.

The results of the long difference estimation are reported in Table 9. For the estimation performed on the U.S. sample, the beginning period, A, includes the first four years, 1995-1998, while the last period, B, includes the final four years, 2012-2015. For the estimation performed on the Colombia sample, the beginning period, A, includes the first two years, 2007-2008, while the last period, B, includes the final two years, 2012-2013.

The results presented in Table 9 suggest that changes in export unit weight are positively correlated with changes in GDP per capita and negatively correlated with changes in oil price-adjusted distance. While these results support my proposition regarding weight-based quality specialization, they exhibit a weaker statistical significance than the cross-sectional results reported in Table 8. Also, in line with the existing literature on quality specialization, the changes in export value-to-weight ratio are positively correlated with changes in both GDP per capita and oil price-adjusted distance.

[27] The use of oil price-adjusted distance, $\text{Dist}_j \times P_{\text{oil},t}$, as a time varying regressor is motivated by von Below and Vézina (2016).

Table 9: The International Variation in Export Unit Weights and Value-to-Weight Ratios

	Colombia			United States		
Regressor	Δunit weight	Δvalue/weight	Δunit price	Δunit weight	Δvalue/weight	Δunit price
ΔDistance$\times$Oil	-0.091	0.534^{***}	0.444^{***}	-0.048^{***}	0.281^{***}	0.233^{***}
	(0.094)	(0.088)	(0.116)	(0.008)	(0.005)	(0.008)
ΔGDP p/c	1.249^{***}	0.571	1.820^{***}	0.018^{*}	0.047^{***}	0.065^{***}
	(0.415)	(0.424)	(0.542)	(0.010)	(0.006)	(0.010)
Observations (rounded)		35,000			149,000	
GDP control		YES			YES	
Transport mode control		YES			YES	
FTA control		YES			YES	
Remoteness control		YES			YES	
Tariff control		YES			YES	
Fixed Effects		HS10 product			HS10 product	

Note: The estimating equation is Equations 11. All long-differenced variables are in logs. All standard errors are clustered by country of origin and year. *** denotes significance at the 1% level; and * denotes significance at the 10% level.

5 Implications for the Existing Literature

The patterns documented in this paper have two key implications for the existing literature. First, the results presented in Section 4 suggest that focusing on value-to-weight ratios overlooks an important component of product quality that is readily observable in the data. Many widely-used datasets (like the BACI data compiled by CEPII) have a tendency to report value-to-weight ratios but not unit weight levels. As a result, most of the empirical research on international quality specialization has focused on value-to-weight ratios as a proxy for quality. While this focus is well-grounded; it can be easily enhanced given the modern structure of customs data.

Weight-based quality specialization can also reconcile existing evidence on the Washington Apples Effect. On one hand, studies that analyze the spatial variation in value-to-weight ratios have found strong support for the Washington Apples Effect (e.g., Baldwin and Harrigan (2011)). On the other hand, studies that analyze the spatial variation in direct measures of quality or unit prices find less conclusive evidence for the same effect (e.g., Crozet et al. (2012)). This apparent tension can be due to distance having countervailing effects on the value-to-weight ratio and unit weight of exports.

The Credibility of the Iceberg Trade Cost Assumption. The second implication concerns Fact 4 from Section 2, which is that transport costs can be modeled as a *quasi-iceberg* cost for an important class of traded goods. This finding can be encouraging for the quantitative trade literature that often models transport costs as an iceberg cost. To make this point formally, consider a perfectly competitive multi-industry quantitative trade model, featuring $j, i = 1, ..., N$ countries and $k = 1, ..., K$ industries.[28] The utility of the representative consumer in country i is given by $U_i = \prod_{k=1}^{K} \left(\sum_{j=1}^{N} \alpha_{ji,k}^{1-\varrho_k} q_{ji,k}^{\varrho_k} \right)^{e_{i,k}/\varrho_k}$, where $\varrho_k \in (0, 1)$ and the subscript ji, k indexes an industry k good that is produced in country j and consumed in country i. $e_{i,k}$ denotes the constant share of expenditure on industry k, while $\alpha_{ji,k}$ accounts for taste shifters and non-tangible trade barriers that apply to variety ji, k. Utility maximization implies that the share of expenditure on variety ji, k is

$$\lambda_{ji,k} = \frac{\alpha_{ji,k} p_{ji,k}^{-\epsilon_k}}{\sum_{n=1}^{N} \alpha_{ni,k} p_{ni,k}^{-\epsilon_k}},$$

where $\epsilon_k = \varrho_k / (1 - \varrho_k)$ and $p_{ji,k}$ is the nominal price of variety ji, k, which is composed of an f.o.b. price, $p_{jj,k}$, plus transport cost: $p_{ji,k} = p_{jj,k} + \mathcal{T}_{ji,k} p_{jj,k}^{\beta_k}$. The transport cost formulation, $\tau_{ji,k} = \mathcal{T}_{ji,k} p_{jj,k}^{\beta_k}$, is analogous to that estimated in Section 2, with $\mathcal{T}_{ji,k}$ encompassing all non-price-related transport cost shifters. Also, recall that this formulation reduces to the exact-iceberg specification if $\beta_k = 1$.

My objective is to compute the gains from a reduction in transport costs under the micro-estimated β_k's and compare them to the gains implied by the iceberg assumption. I formulate this change in terms of the exact hat algebra notation: $\hat{x} \equiv x'/x$. For a given change in transport costs, $\{\hat{\mathcal{T}}_{ji,k}\}$, the change in consumer prices can be expressed as

$$\hat{p}_{ji,k} = (1 - \rho_{ji,k}) \hat{p}_{jj,k} + \rho_{ji,k} \hat{\mathcal{T}}_{ji} \hat{p}_{jj,k}^{\beta_k}$$

where $\rho_{ji,k} \equiv \tau_{ji,k} / p_{ji,k}$ denotes the share of transport costs in the final consumer price. Assuming that (i) markets are perfectly competitive, (ii) production is subject to constant returns to scale, (iii) labor is the only factor of production and is inelastically supplied, and (iv) labor is perfectly mobile across industries within a country but immobile across countries, then $\hat{p}_{jj,k} = \hat{w}_j$, where w_j denotes the wage rate in country j.[29] The change in trade shares can, thus, be expressed as

$$\hat{\lambda}_{ji,k} = \frac{\left[(1 - \rho_{ji,k}) \hat{w}_j + \rho_{ji,k} \hat{\mathcal{T}}_{ji,k} \hat{w}_j^{\beta_k} \right]^{-\epsilon_k}}{\sum_{n=1}^{N} \lambda_{ni,k} \left[(1 - \rho_{ni,k}) \hat{w}_n + \rho_{ni,k} \hat{\mathcal{T}}_{ni,k} \hat{w}_n^{\beta_k} \right]^{-\epsilon_k}}. \tag{12}$$

[28] Previously, I used k to index HS10 product categories. Here, I am using k to denotes industries, which are a more aggregate product category.

[29] To elaborate on the micro-foundation, $p_{ii,k} = a_{i,k} w_i$ where $a_{i,k}$ denotes the constant unit labor cost. Transportation also employs labor from the exporting country with the implicit assumption that the unit labor cost of transportation varies with the price of the transported goods.

The wage change is itself governed by the labor market clearing condition:[30]

$$\hat{w}_i Y_i = \sum_j \hat{\lambda}_{ij,k} \lambda_{ij,k} e_{j,k} \hat{w}_j Y_j. \tag{13}$$

We can combine Equations 12 and 13 to solve for $\hat{w}_i$ given a policy shock $\hat{\mathcal{T}}_{ij,k}$. To do so, we only need data on $\lambda_{ij,k}$, $e_{i,k}$, Y_j and $\rho_{ij,k}$, as well as estimates for ϵ_k and β_k. After solving for $\hat{w}_i$, we can compute the welfare gains from policy as $\hat{W}_i = \hat{w}_i / \prod_k \hat{P}_{i,k}^{e_{i,k}}$, where $\hat{P}_{i,k} = \left[\sum_j \lambda_{ji,k} \hat{p}_{ji,k}^{-\epsilon_k}\right]^{-1/\epsilon_k}$.

To perform this task, I take data on expenditure share and total income from the widely-used World Input Output Database (WIOD, Timmer et al. (2012)), which includes include all 27 members of the European Union and 13 other major economies: Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey, and the United States. See Appendix D for a detailed description of the data and a full list of industries and countries in the WIOD.

While $\rho_{ji,k}$ is directly observable in country-specific import datasets, it is not reported in multi-country datasets like the WIOD.[31] However, as outlined in Appendix D, we can infer $\rho_{ji,k}$ from data on trade flows and distance using a standard gravity estimation. Table 10 reports a summary of these inferred values by industry. Estimates for ϵ_k are taken from Caliendo and Parro (2015) and are also reported in Table 10.

To determine β_k, I estimate Equation 3 separately for each industry. The estimated values are reported in Table 10.[32] In line with Fact 4, transport costs are quasi-iceberg ($\beta_k \approx 1$) in discrete industries such as 'Transport Equipment', 'Machinery', and 'Electronics'. In non-discrete industries, however, the estimated transport cost elasticity, β_k, is systematically below one. This outcome should be expected given that, for non-discrete goods, there is no variation in unit weight that contributes to β_k.

Figure 3 compares the gains from a 25% reduction in transport costs based on the estimated β_k's to the gains from an equal-yield reduction in iceberg transport costs, which correspond to $\beta_k = 1$. The average gains are modestly larger under the estimated transport cost specification. But the differences are somewhat modest: The GDP-weighted gains average around 1.35% under the estimated transport cost specification and 1.30% under the iceberg transport cost specification.

Figure 3 suggests that modeling transport costs as an iceberg cost may be less problem-

[30] The labor market clearing condition, as outlined by Equation 13, implicitly assumes that transportation employs only labor from the origin country.

[31] Following Hummels and Lugovskyy (2006), c.i.f to f.o.b. price ratios are not informative about the transport cost to price ratio either.

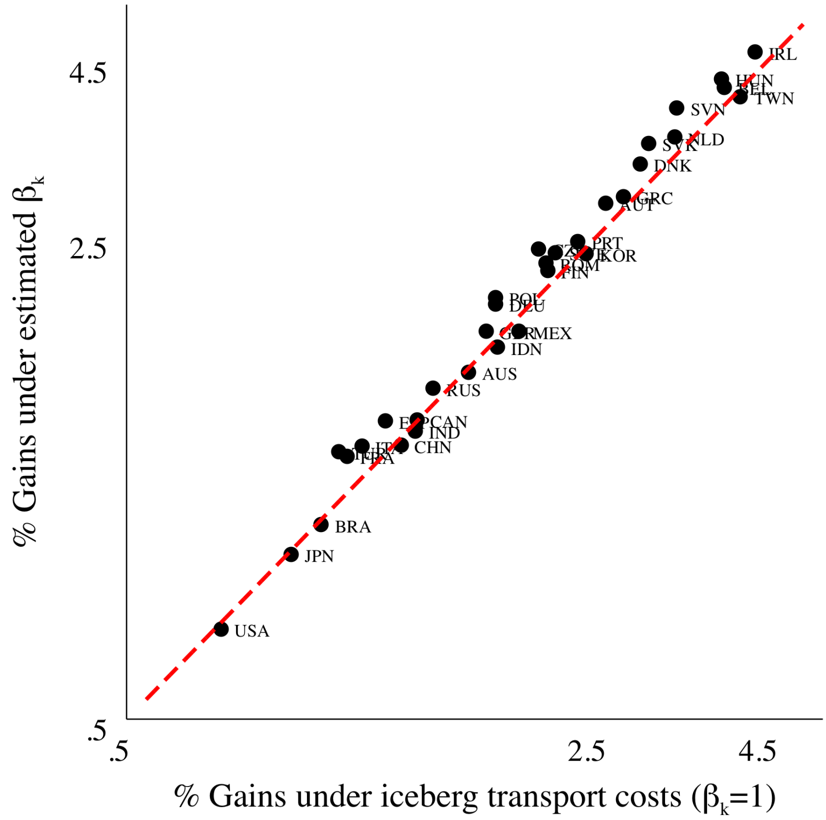
[32] The industry-level estimation of Equation 3 is performed using the full sample of Colombian data, which includes both discrete and non-discrete goods.

Table 10: Industry-level estimation results

				Eq. 3 estimated by Industry	
Sector	ISIC4 codes	ϵ_k	$\rho_{ij,k}^{avg}$	β_k	observations
Agriculture	100-999	8.11	0.05	0.40	96,000
				(0.003)	
Mining	1000-1499	15.72	0.15	0.24	19,300
				(0.066)	
Food	1500-1699	2.55	0.08	0.51	222,500
				(0.029)	
Textiles, Leather, & Footwear	1700-1999	5.56	0.13	0.40	1,086,900
				(0.012)	
Wood	2000-2099	10.83	0.04	0.90	33,700
				(0.041)	
Paper	2100-2299	9.07	0.04	0.70	226,400
				(0.030)	
Petroleum	2300-3399	51.08	0.03	0.29	52,800
				(0.107)	
Chemicals	2400-2499	4.75	0.14	0.34	1,132,800
				(0.008)	
Rubber & Plastic	2500-2599	1.66	0.13	1.02	893,205
				(0.008)	
Minerals	2600-2699	2.76	0.05	0.81	197,178
				(0.020)	
Basic & Fabricated Metals	2700-2899	7.99	0.07	0.65	1,173,000
				(0.009)	
Machinery	2900-3099	1.52	0.21	1.13	2,395,700
				(0.005)	
Electrical & Optical Equipment	3100-3399	10.60	0.09	1.02	2,099,100
				(0.005)	
Transport Equipment	3400-3599	0.37	0.26	1.13	1,156,400
				(0.006)	
N.E.C. & Recycling	3600-3800	5	0.14	0.84	396,000
				(0.009)	

Notes: The trade elasticity values, ϵ_k, are taken from Caliendo and Parro (2015). $\delta_{ij,k}^{avg}$ denotes the (trade-weighted) average transport cost-to-final price ratio in industry k. Estimates for β_k are attained by estimating equation 3 on an industry-by-industry basis using the 2SLS estimator. Robust standard errors are reported in parenthesis.

Figure 3: Gains from reduction in transport costs: iceberg vs. estimated specification



atic than previously thought. To elaborate, most critiques of the iceberg assumption are based on evidence that $\beta_k \ll 1$. They state that if $\beta_k \ll 1$, then a reduction in transport costs shifts demand in favor of low-quality varieties, yielding welfare effects that are different from a reduction in iceberg costs. But, as noted earlier, the evidence that motivate this line of argument overlook the heterogeneity in export unit weights. The analysis behind Figure 3, in comparison, estimates β_k while accounting for the heterogeneity in export unit weights. These estimates are then plugged in to a model that admits cross-national differences in product quality—these differences are implicitly embedded in the observable expenditure and transport cost shares.[33] The final output indicates that welfare implications are rather identical under the estimated and iceberg transport cost specifications.

That being said, the message conveyed by Figure 3 should be interpreted with caution. First, my analysis here is confined to transport costs, whereas the iceberg trade costs (in their standard definition) encompass other barriers to trade. Though, most of the

[33] From the lens of the above model, the heterogeneity in $\lambda_{ji,k}$'s and $\rho_{ji,k}$'s may be driven by cross-national differences in *either* output quality or physical productivity. Under the latter interpretation, if β_k is sufficiently below unity, a reduction in transport costs will shift import demand in favor of high quality (low-ρ) product varieties.

existing evidence against the iceberg specification are based on transport cost data.[34] Second, to simplify the exposition, my counterfactual analysis abstracted from firm-selection effects and non-homothetic preferences for quality. Through these channels, small deviations from the iceberg specification can influence welfare in ways that are not picked up by my rather standard analysis.

6 Conclusions

Research on consumer psychology suggests that physical weight is one of the most defining features of a product, with consumers perceiving heavier goods as higher quality goods in most contexts. In the context of long-distance trade, physical weight also has a profound impact on the cost of transportation. So, it may come at a surprise that mainstream trade theories have paid small attention to modeling and understanding the role of physical weight in the global economy.

Against this backdrop, I uncovered five basic facts concerning the role of physical weight in international trade. Accordingly, I developed a simple model to study what types of characteristics induce firms to manufacture heavier product varieties. The model predicted that firms located in high-wage economies are more likely to supply heavier product varieties, whereas firms located in distant economies are more likely to supply lighter product varieties. To the extent that physical weight determines product quality, these patterns can be perceived as *weight-based quality specialization*. I presented further evidence that supported these predictions.

A withstanding question is how trade liberalization (either through improvements in transport infrastructure or trade agreements) affects the anatomy of weight-based quality specialization. There is exhaustive evidence that firms in advanced countries upgrade their output quality in face of import competition. We know less about whether quality upgrading happens along the weight margin or the intangible margins of quality. These distinctions are important because physical weight and intangible product appeal have dissimilar effects on transport costs.

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[34] A notable exception is Irarrazabal et al. (2015), who evaluate the iceberg specification using the curvature of import demand.

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A Data Appendix

A.1 Restricting the Sample to Discrete Goods

The Colombia import data reports quantity in 10 different units. The vast majority of entries report quantity either in counts, *"UNIDADES O ARTICULOS"*, or in kilograms, *"KILOGRAMO."* The exact composition of the Colombian data is reported in Table 11, which indicates that 50.6% of Colombian imports (in value terms) involve goods that report quantity in counts or its derivatives—these derivatives include pairs of goods, *"PAR,"* and thousands of goods, *"MILLAR."* I classify such goods are *"discrete,"* and restrict my sample to them. Accordingly, goods that report quantity in kilograms or its derivative are not the subject of my analysis, as they do not exhibit a pre-customized, factory-gate unit weight. Instead, consumers can purchase such *non-discrete* goods by the weight.

Table 11: The composition of imports by the unit of measurement.

	The unit in which *quantity* is reported		
Sample	Count & derivatives	KG & derivatives	Other
Colombia Imports	50.6%	40.3%	9.1%
US Imports	56.3%	23.1%	21.6%

Note: In the Colombia sample, discrete goods report quantity in terms of "UNIDADES O ARTICULOS" (count of goods), "PAR" (pairs), and "MILLAR" (thousands). The US features various derivatives of item count, namely, "N", "NO", "DOZ", "DPC", "DPR", "PCS", "PRS", "PK", "HUN", "THS". Similarly, the US data contains various derivatives of kilograms: "K", "KG", "TON", "T", "kg", "GRS", "GM", "GKG", "G", "CYK", "GTN". See https://www.census.gov/foreign-trade/guide/sec4.html#units for a full description of these abbreviations.

The US import data reports quantity in 50 different units. The dataset is compiled and updated by Schott (2008) does not include the units in which quantity is measured. However, the raw database which is accessible from the *"http://www.census.gov/foreign-trade"* reports this information—see Feenstra et al. (2002) for a detailed description of the raw Census import data. Based on this information, Table 11 reports that the vast majority of US imports concern discrete goods that report quantity in counts, *"NO,"* or its derivatives. To provide numbers, 56.3% of US imports (in value terms) involve goods that report quantity in terms of *"NO"* and corresponding units like pairs of goods, *"PRS,"* and dozens of goods, *"DOZ."*[35] As with the Colombia sample, I restrict the US sample exclusively to such *discrete* goods. Finally, it should be noted that, during

[35] When calculating the statistics in Table 11, I drop observations for which the unit of quantity is either missing or unreported (documented as *"X"*). Moreover, some observations concerning discrete goods report quantity in *"D"* and *"P,"* which are short for *"PRS"* and *"DOZ."*

the 1995-2015 period, the HS10 codes underwent multiple revisions (see Pierce and Schott (2012)). This is, however, not problematic for my analysis as I conduct all the estimations with product$\times$year (or even more narrowly-defined) fixed effects.

A.2 Dropping Observations with no Precedent

After restricting the sample to discrete goods, I am left with a total of 12,480,000 observations in Colombia sample and 7,956,000 observations in the US sample. In the Colombia sample, I can construct instruments for variables pertaining to observation s, jkt, only if the Colombian municipality responsible for ordering shipment s, jkt has imported good k from other suppliers (aside from j) in prior years. Considering this, I drop 4,181,000 observations that have no precedent, which leaves me with 8,299,000 observations (out of the original 12,480,000). Similarly, in the case of the US, I can construct instruments for variables pertaining to observation s, jkt, only if the US district responsible for shipment s, jkt has imported good k from other countries (aside from j) in prior years. Considering this, I drop 3,255,000 observations that have no precedent, which leaves me with 4,701,000 observations (out of the original 7,956,000). I do not trim the sample further, but trimming the sample to drop observations that report a total transaction value of \$5,000 or less does not change the estimation results qualitatively. That is, Fact 1-5 can be stated as is, even if I restrict attention to observation with a greater-than-\$5000 value.

A.3 Cleaning Data on Firm's Identity/Name

The names of the exporting firms in the Colombian import dataset are not standardized. There are instances when the same firm is recorded differently due to using or not using the abbreviations, capital and lower-case letters, spaces, dots, other special characters, etc. To standardize the names of the exporting firms, I borrow the following procedure from Lashkaripour and Lugovskyy (2018):

1. I delete all observations with a missing exporting firm's name.

2. I capitalize firms' names and their contact information (which is either email or phone number of the firm).

3. I eliminate abbreviation "LLC," spaces, parentheses, and other special characters (. , ; / @ ' } - & ") from the firms' names.

4. I eliminate all characters specified in bullet 3 plus a few others (# : FAX) from the contact information.

5. I drop observations without contact information (such as, "NOTIENE", "NOREPORTA", "NOREGISTRA," etc.), with non-existent phone numbers (e.g., "0000000000",

"1234567890", "1"), and with six phone numbers which are used for multiple firms with different names (3218151311, 3218151297, 6676266, 44443866, 3058712865, 3055935515).

6. Next, I keep only up to first 12 characters in the firm's name and up to first 12 characters in the firm's contact information (which is either email or phone number). I treat all transaction with the same updated name and contact information as coming from the same firm.

7. I also analyze all observations with the same contact information, but slightly different name spelling. I only focused on the cases in which there are up to three different variants of the firm name. For these cases, I calculate the Levenshtein distance in the names, which is the smallest number of edits required to match one name to another. I treat all export observations as coming from the same firm if the contact phone number (or email) is the same and the Levenshtein distance is four or less.

B Sensitivity Analysis: *Facts 1-5*

In this appendix, I subject the facts presented in Section 2 to several robustness checks. I begin with Fact 2, and its sensitivity to aggregation bias and measurement errors.

B.1 Checking for Aggregation Bias

One may be concerned that Fact 2 is plagued by aggregation bias. That is, one may suspect that there is considerable cross-product heterogeneity in the direction of the cost-weight relationship. To address this concern, I re-run Regression 13 separately for each 6-digit HS6 industry in both the Colombia and US samples. The by-industry estimation results are reported in Table 12. Evidently, Fact 2 is a robust feature of the data, even when documented on an industry-by-industry basis. More specifically, in the case of Colombia, the coefficient $\alpha \equiv \partial \ln p / \partial \ln \omega$ is positive and exhibits a t-statistic of greater than 2 for 1,741 (out of 1,772) HS6 industries. α is negative and significant for only 29 HS6 industries, including "HS871190" (Motorcycles and Cycles) and "620719" (Men's Underwear). That is, in only 29 out of out of 1,772 HS6 industries, lighter goods are more costly to manufacture. Similar patterns are observable in the US data.

B.2 Checking for Measurement Error

The concern about measurement error is that Q is may be measured with significant error. At the same time, it is used to calculate both $\omega = W/Q$ (the explanatory variable in Equation 1) plus $p = V/Q$ (the dependent variable in Equation 1). The bias due to measurement error in the explanatory variable, ω, should be handled by the IV approach as long as the instrument (which uses lagged information on alternative

Table 12: The weight-price relationship by HS6 Industry.

Statistic	Colombia Median	Colombia 1st quartile	Colombia 3rd quartile	United States Median	United States 1st quartile	United States 3rd quartile
$\alpha \equiv \frac{\partial \ln \textit{unit weight}}{\partial \ln p}$	0.86	0.72	0.94	0.76	0.61	0.88
t-stat	35.3	16.2	69.7	31.2	12.4	68.7
Fixed Effect	firm×HS10 product×year			country×HS10 product×year		
No. of HS6 industries	1,772			1,358		
Positive relationship ($\alpha > 0$)	1,731			1,312		
Stat. Sig. at the 95% level	1,760			1,295		

Note: This table estimates Equation 1 separately for various discrete HS6 categories. The standard errors are clustered by HS10 product.

routes) is uncorrelated with the measurement error in Q. There remains, however, the concern that the presence of an error-prone variable Q on both the right-hand- and left-hand-sides of Equation 1, would produce a spurious correlation between p and ω.

To address this latter concern, I document Fact 2 using the following alternative specification:

$$\ln V_{s,jkt} = a_1 \ln W_{s,jkt} + a_2 \ln Q_{s,jkt} + \delta_{jkt} + \epsilon_{s,jkt},$$

where recall that V, W, Q respectively denote total f.o.b. value, total physical weight, and total quantity; while δ_{jkt} controls for *supplier×product×year* fixed effects. The estimation results reported in Table 13 imply that after controlling for total quantity, the total value of imported shipments is strongly related to the total physical weight of the shipment. Given our assumption that markups are constant within *supplier×product×year* cells, the variation in V after controlling for Q, is driven by the marginal cost. So, the estimation results once again reinstate the fact that heavier goods exhibit a higher marginal cost of production.

B.3 Excluding 'Transport Equipment' and 'Electronics'

HS10 product codes belonging to the 'Transport Equipment' and 'Electronics' industries are often broadly-defined, occasionally encompassing a range of objectively different products. Unit weight in my estimation may be, thus, picking up the effect of other tangible product characteristics like screen size or engine power. This issue is not necessarily inconsistent with my theory of weight-based quality specialization but is worth addressing nonetheless. To address this issue, I estimate Equation 1 on a sub-sample of Colombian import that (a) excludes 'Transport Equipments' corresponding

Table 13: Dependent: Total Value ($\ln V_{s,jkt}$)

Regressor (log)	Colombia	United States
Total Weight, W	0.725***	0.655***
	(0.0054)	(0.0038)
Total Quantity, Q	0.177***	0.199***
	(0.0071)	(0.0039)
Within-R^2	0.82	0.83
Observations (rounded)	8,299,000	4,701,000
Controls for transport mode	Yes	Yes
Fixed Effects	firm×HS10×year	country×HS10×year

Note: The independent variable is the unit f.o.b price, $\ln p_{s,jkt}$, and the estimating equation is Equation 1. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

to ISIC codes , and (b) 'Electronics' corresponding to ISIC codes . The results are displayed in Table 14, and reinstate *Fact 2* presented in Section 2.

Table 14: Marginal cost across shipments from the same supplier (dependent: $\ln p$)

	Sample w/o Tansport Eq.		Sample w/o Electronics	
Regressor (log)	OLS	2SLS	OLS	2SLS
Unit weight, ω	0.756***	0.565***	0.765***	0.681***
	(0.0074)	(0.1190)	(0.0068)	(0.1263)
Within-R^2	0.68	...	0.60	...
First-Stage F-stat	...	2,356	...	2,459
Observations (rounded)	7,100,000		6,230,000	
Controls for transport mode	Yes		Yes	
Fixed Effects	firm×HS10×year		country×HS10×year	

Note: The independent variable is the unit f.o.b price, $\ln p_{s,jkt}$, and the estimating equation is Equation 1. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

B.4 Alternative Choice of IV

Here, I investigate the robustness of Facts 3 and 4 to the choice of instruments. To this end, I perform Regressions 2 and 3 with an alternative choice of instrument, which is motivated by the finding in Kugler and Verhoogen (2012) that Colombian firms which import high-quality inputs, produce and export higher quality outputs.

To construct my alternative instrument, I use data on the universe of Colombian exports for the same time period as my import data sample. I then merge the Colombian import and export databases by matching importer and exporter ids. The merge leaves me with 2,630,436 observations. For each observation s, jkt I can identify the Colombian firm (indexed j) responsible for the import order; as well as the lagged unit weight, value-to-weight ratio, and unit f.o.b. price of that firm's exports to foreign market (namely, $\omega_{j,t-1}^{export}$, $v_{j,t-1}^{export}$, and $p_{j,t-1}^{export}$). Accordingly, I instrument for $\omega_{s,jkt}$, $v_{s,jkt}$, and $p_{s,jkt}$, with $\omega_{j,t-1}^{export}$, $v_{j,t-1}^{export}$, and $p_{j,t-1}^{export}$. That is, motivated by Kugler and Verhoogen (2012), I exploit the across shipment variation in the quality of the Colombian importing partner to identify the transport cost parameters

The estimation results under this approach are presented in the Table 15. They reaffirm Facts 3 and 4. That is, the unit cost of transportation increases more rapidly with physical unit weight than the marginal cost of production; as well as the *iceberg* specification provides a semi-accurate reduce-form representation of the transport cost function.

Table 15: Alternative Choice of Instruments (dependent: $\ln \tau$)

	Fact 3		Fact 4	
Regressor (log)	OLS	2SLS	OLS	2SLS
Value-to-weight, v	0.568***	0.025	...	...
	(0.0240)	(0.4974)		
Unit weight, ω	1.069***	1.289***	...	...
	(0.0092)	(0.4718)		
Unit price, p	...	...	0.959***	0.988***
	...	...	(0.0133)	(0.3135)
Within-R^2	0.73	...	0.68	...
First-Stage F-stat	...	179	...	356
Observations (rounded)	2,630,000		2,630,000	
controls for transport mode	Yes		Yes	
control for shipment scale	Yes		Yes	
fixed effects	firm×HS10×year		country×HS10×year	

Note: The independent variable is the unit transport cost, $\ln \tau_{s,jkt}$, and the estimating equation is Equations are 2 and 3. All standard errors are clustered by HS10 product. *** denotes significance at the 1% level.

C Demand Function Estimation

This appendix describes the methodology used to estimate the demand function and the unobservable quality in Section 2.

Colombia Data. The firm-level import demand estimation conducted on the Colombia data is borrowed from Lashkaripour and Lugovskyy (2018). The estimating equation can be expressed as follows:

$$\ln q_{jkt} = \varepsilon_k \ln \tilde{p}_{jkt} + \sigma_k \ln \lambda_{jkt} + \varphi_{jk} + \varphi_{jkt},$$

where $\tilde{p}$ denotes the consumer price, which is the sum of the f.o.b. price plus transport costs and import taxes. The term λ_{jkt} denotes variety jkt's nest-share, which is the expenditure on variety jkt relative to the total expenditure on all varieties from country ℓ (which is firm j's country of origin). Namely,

$$\lambda_{jkt} \equiv \frac{\tilde{p}_{jkt} q_{jkt}}{\sum_{j \in \mathcal{J}_{\ell kt}} \tilde{p}_{jkt} q_{jkt}},$$

where $\mathcal{J}_{\ell kt}$ where denotes the set of all firms exporting product k from country ℓ in year t. The inclusion of λ_{jkt} on the right-hand side controls for the possibility that the cross-national and sub-national elasticities of substitution may differ. Finally, φ_{jk} is a *firm*$\times$*product* fixed effect, and φ_{jkt} accounts for *firm*$\times$*product*$\times$*year* deviations in product quality, plus measurement error. Taking first-differences from the above equation eliminates the *firm*$\times$*product* fixed effect, leaving us with following estimating equation:

$$\Delta \ln q_{jkt} = \varepsilon_k \Delta \ln \tilde{p}_{jkt} + \sigma_k \Delta \ln \lambda_{jkt} + \epsilon_{jkt}, \tag{14}$$

where $\epsilon_{jkt} \equiv \Delta \varphi_{jkt}$. To estimate the above equation, we need a plausibly exogenous cost-shifter, z_{jkt}, that is correlated with $\tilde{p}_{jkt}$, but orthogonal to ϵ_{jkt}. To construct z_{jkt}, I first compile a monthly database on aggregate exchange rate movements. I let $\Delta e_{\ell t}(m)$ denote the change in country ℓ's exchange rate with Colombia in month m in year t. Correspondingly, I let $x_{jkt}(m) = p_{jkt}(m)\, q_{jkt}(m)$ denote firm j's sales of product k to Colombia in month m of year t. Interacting the data on $\Delta e_{\ell t}(m)$ with lagged data on $x_{jkt}(m)$, allows me to construct the following shift-share instrument for every variety jkt exported to Colombia from country ℓ (i.e., $j \in \mathcal{J}_{\ell kt}$):

$$z_{jkt} = \sum_{m \in \mathcal{M}} x_{jkt}(m) \cdot \Delta e_{\ell t-1}(m), \quad j \in \mathcal{J}_{\ell kt}$$

where $\mathcal{M}$ denotes the set of all months in a fiscal year. To elaborate, the above instrument measures the firm-level exposure to exchange rate shocks using lagged data on firm-level sales and concurrent data on aggregate exchange rate movements. Additionally, and following Khandelwal (2010), the change in the number of active firms in set $\mathcal{J}_{\ell kt}$, plus the change in the total number of product categories served by firm j are employed as an instrument for $\Delta \ln \lambda_{jkt}$.

U.S. Data. The country-level import demand estimation conducted using the US data is borrowed from Khandelwal (2010). The estimating equation can be expressed as follows:

$$\ln q_{jkt} = \varepsilon_k \ln \tilde{p}_{jkt} + \sigma_k \ln \lambda_{jkt} + \varphi_{jk} + \varphi_{jkt}, \tag{15}$$

where $\tilde{p}_{jkt}$ denotes the unit price of country j's exports to the US in product category k, in year t (inclusive of trade taxes and transport costs). λ_{jkt} denotes variety jkt's nest-share, but unlike before the nest is now an HS10 product category. That is, λ_{jkt} denotes the expenditure on variety jkt relative to the total expenditure on all varieties from product category k. Namely,

$$\lambda_{jkt} \equiv \frac{\tilde{p}_{jkt} q_{jkt}}{\sum_{j \in \mathcal{J}_{kt}} \tilde{p}_{jkt} q_{jkt}}.$$

The term $\sigma_k \ln \lambda_{jkt}$, therefore, controls for the possibility that the cross-product and within-product elasticities of substitution may differ. Finally, φ_{jk} is a *country*$\times$*product* fixed effect, and φ_{jkt} accounts for *country*$\times$*product*$\times$*year* deviations in product quality, plus measurement error.

To estimate the above equation, I use tariffs as an exogenous cost-shifter to instrument for the consumer price, $\tilde{p}$. I also use the total number of countries serving nest k and the total number of nests served by country j in a given industry as an instrument for λ_{jkt}.

Estimation Results. Table 16 reports the import demand parameters estimated using the above approach. The reported results correspond to the pooled estimation, where all observations are pooled together under the assumption that $\varepsilon_k = \varepsilon$ and $\sigma_k = \sigma$. Relatedly, the results reported in Table 7 of the main text are also produced based on these pooled estimates presented in Table 16. As an alternative, I also estimate the import demand parameters by an industry-by-industry basis using the widely-used WIOD (World Input-Output Database) industry classification. Fact 5 can be stated as is, once documented using this latter approach.

Relationship to Hummels and Klenow (2005). Before concluding this appendix, a comparison between Khandelwal's (2010) and Hummels and Klenow's (2005) method for measuring product quality is in order. To draw this comparison, let me temporarily abstract from variety-specific indexes. Consider a non-parametric representation of

Table 16: Pooled Import Demand Function

	Colombia		United States	
Variable (log)	IV	OLS	IV	OLS
Price, ε	-2.26***	0.06***	-2.23***	0.94***
	(0.062)	(0.001)	(0.054)	(0.021)
Nest share, σ	0.38***	0.88***	0.52***	0.60***
	(0.009)	(0.000)	(0.018)	(0.047)
First-Stage F-stat	177.99	...	435.6	...
Within-R^2	...	0.82	...	0.46
Observations	1,347,000		1,927,000	

Notes: *** denotes significance at the 1% level. The estimating equations are 14 and 15. Standard errors in parentheses are clustered by product-year. The estimation is conducted with HS10 product-year fixed effects in the case of Colombia and with Country-year fixed effects in the case of the US.

demand in country i, namely, $q = \mathcal{D}_i(\tilde{p}/\varphi; \mathbf{X})$, which assumes isomorphism between quality and quantity. Vector $\mathbf{X}$ in this representation, encompasses observable product characteristics other than $\tilde{p}$ and φ. Assuming that demand is multiplicatively separable, we can produce the following decomposition of the demand function:

$$q = \mathcal{D}_i(\tilde{p}/\varphi; \mathbf{X}) = D_i(\tilde{p}; \mathbf{X}) \times \underbrace{\Phi(\varphi)}_{\tilde{\varphi}},$$

with $\Phi'(.) > 0$ and $\tilde{\varphi}$ being an order-preserving transformation of φ. Khandelwal's (2010) method estimates the function, $D_i(\tilde{p}; \mathbf{X})$, using data on q, $\mathbf{X}$, and $\tilde{p}$. It, then, infers quality from the estimated demand function as

$$\hat{\tilde{\varphi}} = q/\hat{D}_i(\tilde{p}; \mathbf{X}).$$

In comparison, Hummels and Klenow's (2005) method inverts an estimated demand function to measure quality-adjusted prices. Then, quality is inferred from the *nominal-to-quality-adjusted price* ratio:

$$\tilde{p}/\varphi = \mathcal{D}_i^{-1}(q; \mathbf{X}) \implies \hat{\varphi} = \tilde{p}/\hat{\mathcal{D}}_i^{-1}(q; \mathbf{X}).$$

Comparing the two methods, it is immediate that Khandelwal's (2010) method is akin to that of Hummels and Klenow (2005). Both methods should also deliver similar quality estimates provided that the underlying demand function is properly estimated.

Table 17: The relationship between unit weight and quality by industry.

		Colombia		United States	
Sector	ISIC4 codes	Overall R^2	% unit weight	Overall R^2	% unit weight
Machinery	2900-3099	0.92	73.5%	0.93	82.7%
Electrical & Optical Eq.	3100-3399	0.91	63.7%	0.94	77.1%
Transport Equipment	3400-3599	0.86	68.5%	0.88	73.9%
Textiles, Leather & Footwear	1700-1999	0.66	36.3%	0.77	37.7%
Wood	2000-2099	0.90	79.4%	0.93	73.9%
Paper	2100-2299	0.83	35.7%	0.90	66.5%
Rubber & Plastic	2500-2599	0.87	66.7%	0.85	76.1%
Minerals	2600-2699	0.87	61.4%	0.93	73.0%
Basic & Fabricated Metals	2700-2899	0.86	47.2%	0.93	76.3%
N.E.C. & Recycling	3600-3800	0.88	56.6%	0.88	70.0%

Note: This table estimates Equation 4 separately for various industries. The columns labeled "% unit weight" reports the per-cent of the total R^2, which is attributable to unit weight, ω, based on the Shapely decomposition.

C.1 Decomposing the Determinant of Product Quality by Industry

Table 7 in the main text decomposed the determinants of product quality using the pooled sample. Here, I perform the same exercise on an industry-by-industry basis. To this end, I estimate Equation separately for each industry K, based on the WIOD industry classification:

$$\hat{\varphi}_{jkt} = b_{\omega,K} \ln \omega_{jkt} + b_{v,K} \ln v_{jkt} + \delta_t + \epsilon_{jkt} \quad k \in K.$$

The above regression is estimated for all WIOD industries that based on Table 1 involve more than 5% discrete product categories. The estimation results are reported in Table 17. For each sample, the first columns reports overall R^2 of the industry-level regression. The second column reports per-cent of the overall R^2 that is attributable to unit weight, ω, based on the Shapley decomposition. Evidently, for 'Textiles' physical weight is a much weaker determinant of output quality than for 'Machinery'.

D Details of the Quantitative Analysis

Data Description. My main data source is the 2008 edition of the World Input-Output Database (WIOD, Timmer et al. 2012). The database covers 35 industries and 40 countries, which account for more than 85% of world GDP, plus an aggregate of the rest of the world. The countries in the sample include all 27 members of the European

Union and 13 other major economies, namely, Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey, and the United States. The 35 industries in WIOD database include 15 tradable industries and 20 service-related industries—see Tables 18 and 19 for a thorough description of countries and industries used in the analysis. For each two countries, i, and j, the WIOD reports total spending by country i on goods produced by country j in industry k,namely $X_{ji,k}$. With this information, we can compute total expenditure, $Y_i = \sum_k \sum_j X_{ji,k}$, as well as expenditure shares, $\lambda_{ji,k} = X_{ji,k}/Y_i$, and $e_{i,k} = \sum_j \left(X_{ji,k}\right)/Y_i$. Following Costinot and Rodríguez-Clare (2013), I aggregate the data into 32 countries and an aggregate of the result of the world, plus 15 tradable industries and the and an aggregate of service sector. Also, to make the data consistent my theoretical framework, I purge the data from trade imbalances, closely following the methodology in Costinot and Rodríguez-Clare (2013).

Gravity Estimation. To back out the ratio $\tilde{\rho}_{ji,k} \equiv 1 - \rho_{ji,k} = p_{jj,k}/p_{ji,k}$, I appeal to the gravity equation, which can be expressed as

$$X_{ji,k} = \alpha_{ji,k} p_{jj,k}^{-\epsilon_k} \tilde{\rho}_{ji,k}^{\epsilon_k} P_{i,k}^{\epsilon_k} Y_{i,k},$$

where $X_{ji,k} \equiv p_{ji,k} q_{ji,k}$ denotes country i's expenditure on country j's varieties in industry k. I impose the identifying assumption that the taste parameter,

$$\alpha_{ji,k} = \alpha_{j,k}^{\mathbb{1}\{j \neq i\}} + \varepsilon_{ji,k},$$

features a systematic home-bias term, $\alpha_{j,k}$, that uniformly applies to all foreign varieties as well as an idiosyncratic term, $\varepsilon_{ji,k} \sim N(0, \sigma_k)$. I also assume that $\tilde{\rho}_{ji,k}$, which is by definition equal to 1 minus the share of transport costs in the final price, is proportional to distance: $\tilde{\rho}_{ji,k}^{\epsilon_k} = \tilde{\rho}_{j,k} \text{Dist}_{ji}^{b_k}$. Applying these assumptions, yields the following log-linear gravity equation

$$\ln X_{ji,k} = \Omega_{j,k} + \Phi_{i,k} + \alpha_{j,k}^{\mathbb{1}\{j \neq i\}} + b_k \ln \text{Dist}_{ji} + \varepsilon_{ji,k}, \tag{16}$$

where $\Omega_{j,k} \equiv \tilde{\delta}_{j,k} p_{jj,k}$ is an exporter fixed effect and $\Phi_{i,k} = P_{i,k}^{\epsilon_k} Y_{i,k}$ is an importer fixed effect. Estimating the above equation determines $\tilde{\rho}_{ji,k}$ up-to a trade elasticity, ϵ_k, and $\tilde{\rho}_{j,k}$. I take the trade elasticity parameters for each industry from Caliendo and Parro (2015), and pin down $\tilde{\rho}_{j,k}$ by setting $\tilde{\rho}_{jj,k} = 1$. I adopt an NLLS estimator as in Anderson and Van Wincoop (2004), but using a PPML estimator to accommodate zeros and account for heteroskedasticity in the error terms yields qualitatively similar results.

Computing the Gains from Transport Cost Reduction. After inferring $\{\rho_{ji,k}\}$ from the gravity estimation, we can determine the welfare gains from a reduction, $\hat{\mathcal{T}}_{ij,k} = 0.75$, in transport costs by solving the following system that combines Equations 12 and 13:

$$\hat{w}_i Y_i = \sum_{j=1}^{33} \frac{\lambda_{ij,k}\left[(1-\rho_{ij,k})\hat{w}_i + 0.75 \times \rho_{ij,k}\hat{w}_i^{\beta_k}\right]^{-\epsilon_k}}{\sum_n \lambda_{nj,k}\left[(1-\rho_{nj,k})\hat{w}_n + 0.75 \times \rho_{nj,k}\hat{w}_n^{\beta_k}\right]^{-\epsilon_k}} e_{j,k}\hat{w}_j Y_j$$

The above system involves $N = 33$ unknown wage changes, $\{\hat{w}_i\}$, and requires data on $\{\lambda_{ij,k}\}$, $\{e_{j,k}\}$, and $\{Y_j\}$, which are readily reported in the WIOD database. After solving this system, we can compute the welfare gains from transport cost reduction as:

$$\%\Delta\text{Welfare}_i = 100 \times \left(\frac{\hat{w}_i}{\prod_{k=1}^{16}\left(\sum_{j=1}^{33}\lambda_{ji,k}\left((1-\rho_{ji,k})\hat{w}_j + 0.75 \times \rho_{ji,k}\hat{w}_j^{\beta_k}\right)^{-\epsilon_k}\right)^{-e_{i,k}/\epsilon_k}} - 1 \right).$$

Table 18: List of countries in quantitative analysis

Country name	**WIOD code**	**Economic Region**
Australia	AUS	Australia
Brazil	BRA	Brazil
Canada	CAN	Canada
China	CHN	China
Indonesia	IDN	Indonesia
India	IND	India
Japan	JPN	Japan
Korea	KOR	Korea
Mexico	MEX	Mexico
Russia	RUS	Russia
Turkey	TUR	Turkey
Taiwan	TWN	Taiwan
United States	USA	United States
Austria	AUT	European Union
Belgium	BEL	
Bulgaria	BGR	
Cyprus	CYP	
Czech Republic	CZE	
Germany	DEU	
Denmark	DNK	
Spain	ESP	
Finland	FIN	
France	FRA	
United Kingdom	GBR	
Greece	GRC	
Hungary	HUN	
Ireland	IRL	
Italy	ITA	
Netherlands	NLD	
Poland	POL	
Portugal	PRT	
Romania	ROM	
Slovakia	SVK	
Slovenia	SVN	
Sweden	SWE	
Estonia	EST	
Latvia	LVA	
Lithuania	LTU	
Luximburg	LUX	
Malta	MLT	
Rest of the World	RoW	Rest of the World

Table 19: List of industries in quantitative analysis

WIOD Sector	Sector's Description	Trade Ealsticity (Caliendo-Parro)
1	Agriculture, Hunting, Forestry and Fishing	8.11
2	Mining and Quarrying	15.72
3	Food, Beverages and Tobacco	2.55
4	Textiles and Textile Products Leather and Footwear	5.56
5	Wood and Products of Wood and Cork	10.83
6	Pulp, Paper, Paper , Printing and Publishing	9.07
7	Coke, Refined Petroleum and Nuclear Fuel	51.08
8	Chemicals and Chemical Products	4.75
9	Rubber and Plastics	1.66
10	Other Non-Metallic Mineral	2.76
11	Basic Metals and Fabricated Metal	7.99
12	Machinery, Nec	1.52
13	Electrical and Optical Equipment	10.60
14	Transport Equipment	0.37
15	Manufacturing, Nec; Recycling	5.00
16	Electricity, Gas and Water Supply Construction Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods Hotels and Restaurants Inland Transport Water Transport Air Transport Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies Post and Telecommunications Financial Intermediation Real Estate Activities Renting of M&Eq and Other Business Activities Education Health and Social Work Public Admin and Defence; Compulsory Social Security Other Community, Social and Personal Services Private Households with Employed Persons	5.00