

Income Distribution, Quality Sorting and Trade*

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Abstract

Product quality has been highlighted as an important determinant of trade in recent empirical and theoretical contributions. However, a major limitation for a thorough understanding of these patterns is the lack of direct measures of product quality. In this paper, I construct a new dataset for the Chilean wine industry that is unique in its ability to offer firm-product level measures of quality. Quality measures at this level of disaggregation are typically not available; I use this information to provide novel evidence on how firms vary the quality of their export bundle across markets. The patterns I derive in the data suggest an important role for income distribution in explaining within-firm quality flows. Accordingly, I develop a stylized quality model featuring non-homothetic quality demand and heterogeneous consumers' income. The model predicts that in countries with higher income dispersion, firms tend to skew their exports towards products of higher quality. This effect tends to be weaker in countries with higher average income. I use the Chilean wine data to illustrate the main mechanism. In line with the model's main prediction, I find that firms tend to export proportionally more high-quality products to countries with higher levels of income dispersion. I find this effect to be quantitatively more important in low- and middle-income countries.

JEL: F12, F14, J31, L11

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1 Introduction

Over the last decade, a growing body of empirical and theoretical research has examined the role of product quality in explaining trade patterns. Product quality has been highlighted as a likely factor explaining why exporting firms tend to ship relatively more expensive goods, and charge higher prices for them, in rich countries (Hallak, 2006; Baldwin and Harrigan, 2011; Manova and Zhang, 2012). A major limitation for a thorough understanding of these patterns is the lack of direct measures of product quality. Product quality is ultimately unobservable, and the typical proxies used in the literature – e.g., unit values defined over generic product categories – are subject to important biases. First, differences in unit values reflect not only differences in quality, but also in markups. Second, existing studies typically observe product categories rather than clearly identified varieties. For example, products as diverse as wine are often summarized in a single category. This leads to a composition effect of the exported product bundle: Selling relatively more high-price products – either because the markup is higher or the product has different attributes, such as size or capacity – to a given destination would be (mistakenly) interpreted as an increase in product quality.

This paper advances in our understanding of firm-level quality trade patterns, both empirically and theoretically. On the empirical side, I construct a unique dataset for the Chilean wine industry that contains detailed information on the attributes of all exported wine varieties. A particularly attractive feature of this dataset is that the information is not restricted to pre-defined product categories as in the previous literature, but instead is presented in terms of well-defined varieties.¹ This property of the data allows me to derive quality measures that does not suffer from aggregation issues, and to provide new insights on how firms adjust the quality composition of their exported bundle according to the characteristics of each market.² I show that product aggregation is particularly pervasive when analyzing firm-level export flows, both in terms of destinations and prices. Varieties are typically available in only a subset of the universe of destinations served by firms within the corresponding product category, and unit values computed over product categories accounts for a small fraction of overall variety-level price dispersion. These findings suggest that firms tend to vary in a systematic way the composition of their export bundle shipped across des-

¹The dataset provides information, for each export shipment, of the exporting winery, the brand name printed in the label, the wine grape (e.g., *Cabernet Sauvignon* or *Merlot*), the vintage of the wine (if any), among other attributes. The level of disaggregation of the data is comparable to bar-code data, but the price and exported volume reported in the wine data corresponds to *free-on-board* (F.O.B) instead of retail values.

²In a closely related paper, Crozet, Head, and Mayer (2012) provide empirical evidence on the quality interpretation of Melitz (2003) using expert's quality ratings for the the French Champagne industry as quality measures. However, their quality measures only varies across firms, impeding them to analyze within-firms quality variation across export destinations.

tinations, and that even if prices were perfect measures of product quality, computing them at the more aggregate level would most likely provide just a partial picture of cross-country firm's quality flows.

Next I document a new fact that serves as motivation for the model I develop in the theory section. I show that varieties that are higher in firms' revenue hierarchy tend to be relatively cheaper: in over three-fourths of the firms, the top selling product in terms of revenues is ranked fifth or below in terms of price.³ The fact that each variety's revenue share decreases with price is hard to reconcile with quality-based trade models with representative consumers. Under common parameterizations, these models imply that product quality increases both revenues and prices, contradicting the finding I document in this paper (e.g. Baldwin and Harrigan, 2011; Kugler and Verhoogen, 2012, among others).⁴ I argue that the previous literature, by abstracting from consumer heterogeneity, fail to capture a key element of quality demand: different individuals may optimally choose to consume different quality levels, depending on their income level. In other words, it is not merely average income, but the entire distribution of income that matter for trade. I use this as the main motivation for my theoretical model, where consumer's heterogeneity plays a predominant role.

I then present a simple demand-driven quality model to analyze the role of income distribution in shaping firm's quality decisions across export destinations. The model features non-homothetic demand for quality, heterogeneous consumers, and heterogeneous firms. As in Fajgelbaum et al. (2011), I assume a complementarity between the consumption of a homogeneous good and the quality of vertically differentiated varieties: richer consumers value quality of the differentiated good more. This leads to sorting of consumers into quality segments: rich individuals consume high quality, middle-income individuals consume low quality, and poor consumers purchase none of the differentiated good. The basic intuition behind this result is that, although high quality is desirable for all customers, only a fraction of them can afford it because of its higher price. If consumers are heterogeneous in income, the aggregate demand for each quality level depends on the relative size of the group of consumers that value the particular quality level *and* can afford it. Since aggregate demand for each quality level determines the actual quality mix of firms in each country, it follows that firms' quality allocation across destinations depends not only on the

³See Manova and Zhang (2013) for related evidence using custom-level data from Chinese manufacturing exporters. In my data it is not possible to establish product hierarchies within a firm, because the data consists of a single 6-digit HS code. For comparison, I construct figures for the beverages industry and the manufacturing sector, and show that in these sectors the pattern is considerably weaker.

⁴In principle, revenues may increase or decrease with quality, depending on the sensitivity of marginal costs and product valuation with respect to quality. However, as Khandelwal (2010), and Antoniadou (2013) show, for products with a large scope for quality differentiation – such as wine –, both revenues and prices increase with product quality, contradicting the finding I document in this paper.

average income of the country, but on the entire distribution of income of the country as well.

The model I present differs from the previous literature in at least two directions. First, I assume that the choice of vertical and horizontal attributes is made at different stages: consumers first decide the quality level of the bundle of horizontally differentiated varieties, and then the mix of varieties that compose the bundle. This differs from related quality studies, where quality is modeled as a parameter in models with horizontally differentiated varieties and representative consumers, in the spirit of Melitz (2003).⁵ As I explained above, this type of models predicts that firm revenues and demand are higher for high-quality products, which contradicts the pattern in the data. Second, my model features a richer environment for firms, with simultaneous production in multiple quality segments. This feature is a key innovation of my paper, and is crucial for allowing firms to vary the composition of their export bundle across export destinations. By assuming that firms produce a single version of a product, the previous literature ruled quality differences of the product bundle exported to each destination.⁶ As I show in this paper, this feature is not consistent with the data: in fact, firms systematically vary the quality composition of their exported bundle across destinations, and this variation tends to be correlated with the characteristics of the importing country.

To solve the model, I assume that income within each country is Pareto distributed. Despite recent criticism,⁷ the Pareto distribution allows me to illustrate the main mechanism of the model in an analytically convenient way, since in this distribution variations in average income and income dispersion can be directly linked to the values of the underlying Pareto parameters.⁸ The main prediction of the model suggests that in countries with higher income dispersion, firms tend to skew their exports towards products of higher quality. This effect is nonlinear and depends on the average income of the country. In poor countries, the effect tends to be stronger, while in rich countries the effect is weaker. The intuition for this result follows from the fact that in poor countries, higher income dispersion translates into more rich consumers. In contrast, in rich countries, higher income dispersion implies not only more relatively rich consumers, but also more

⁵There is a prolific literature using extensions of Melitz (2003) for studying product quality in international trade (see Baldwin and Harrigan, 2011; Kugler and Verhoogen, 2012, among others). More recently, Manova and Zhang (2013) and Eckel et al. (2010) develop quality extensions to the multi-product version of Melitz's model, presented in Mayer et al. (2014).

⁶Fajgelbaum et al. (2011) develop a model with a qualitatively similar demand environment. However, since their focus is on country patterns of vertical specialization, their framework provides no insight on how demand conditions affect exporters' quality export choice.

⁷A growing body of literature has pointed out that the income distribution of countries is better described by lognormal or mixtures of other distributions, such as Gamma, Beta, and Weibull.

⁸This is in contrast with Fajgelbaum et al. (2011), where the main analysis is performed assuming generic income distributions. By assuming a particular distribution, I am able to provide more detailed insights on the conditions under which income inequality may affect relative product quality demand.

poor consumers. Since in the model, quality demand is driven by the aggregate mass of rich and poor consumers, income dispersion tends to have a stronger effect within the group of relatively poor countries. The model also has implications for the effect of country size and average income on firms' quality patterns. According to the model, the profitability of exporting any products increases with country size and average income, but the effect is relatively stronger for low-quality varieties. Since richer and larger countries are more profitable in all quality segments, consumers in these countries have more access to high- and low-quality varieties in absolute terms.

Validating the predictions of the model is a particularly challenging task, because product quality is ultimately unobservable, and common trade datasets do not allow for identifying the attributes of individual varieties. I avoid the above-mentioned limitations of unit values by using the Chilean wine dataset to test the main prediction of the model. The wine industry is particularly well suited for verifying the validity of the main mechanisms of the model, because (1) it features a high degree of vertical product differentiation, and (2) firms are predominantly export-oriented – over two thirds of wine production is exported. Importantly, this dataset allows me to define measures of quality that are not subject to compositional effects. The data I use contains detailed information on the attributes of each exported wine variety: brand name, wine grape (e.g., *Cabernet Sauvignon* or *Merlot*), vintage, domain of origin, and bottle capacity, among other attributes. This allows me to identify products with a high degree of confidence, and to work with price measures that are virtually perfect proxies for the actual transaction price.⁹ This feature of the data is extremely important in my empirical setting, because it allows me to analyze the within-firm quality variation across countries, controlling for variable markups and compositional effects, which are commonly not considered in other studies.

The model suggests that the relevant measure of income distribution is the share of the population consuming high-quality products. Since such information cannot easily be derived from readily available measures of income inequality – such as the Gini index – I estimate the income distributions for the 104 countries in my sample and derive the share of relatively rich consumers that are likely to purchase high-quality products in each country. I use these measures to check whether the main mechanism of the model is observed in the data.

The data lends strong support to the main predictions of the model. I document three main findings. First, firms export higher volume and more products to larger and richer countries. However, in relative terms, firms tend to skew their exports towards low-quality products. This is consistent

⁹The price I use in this paper is still a unit value, since it is calculated as the weighted average of all shipments over a year. Thus, the price measure will fail to identify price variations within a year or within countries (which could happen if firms' prices discriminate across regions of a country). However, this is not a limitation for my analysis, because I am not interested in studying within-, but rather across-country annual patterns.

with the idea that when income distributions are positively skewed, an increase in the size or average income increases relatively more for the fraction of middle-income consumers than for rich consumers. Second, firm-level exports of high-quality products are relatively higher in countries with a smaller middle class. Third, consistent with the main prediction of the model, I find the effect of income distribution to be quantitatively relevant only for middle- and low-income countries. I estimate a threshold income of about US\$22,000 – roughly the income level of Slovenia in the year 2005 – below which the effect is quantitatively important.

The rest of the paper is organized as follows. The next section shows how my paper relates to the previous literature. Section 3 provides general background on the wine industry, discusses the main features of the dataset I use in this paper, and presents the stylized facts that serve as the motivation for the theoretical model. Section 4 presents the model and the main testable empirical predictions. Section 6 discusses the empirical strategy and presents the main empirical results. Section 7 concludes.

2 Related Literature

My paper fits within a growing literature that studies the relationship between product quality and trade. The early findings in Schott (2004), Hummels and Klenow (2005), and Hallak (2006) of a positive relationship between importer per capita income and product unit value paved the road for posterior, firm-level empirical work, which confirmed the positive relationship found in country-level studies.¹⁰ Subsequent work focused on testing the implications of models of firm-level quality heterogeneity based on Melitz (2003). Baldwin and Harrigan (2011) propose a model where high-quality firms are also the most competitive firms, and show evidence supporting a positive relationship between unit values and distance, and a negative relationship between importer size and remoteness.¹¹ Kugler and Verhoogen (2012) provide additional support to the idea that it is costly to produce quality. Their model implies that more productive firms use more expensive input and produce more expensive outputs. This prediction is verified by the authors using Colombian firm-level data, and also by Manova and Zhang (2012) for the case of China. In contrast to these contributions, my focus is on within-firm quality patterns. Instead of assuming that firms produce a single product to each destination, I allow them to produce simultaneously in different quality segments, and to vary the quality composition of their export bundle across export destinations. This allow me to understand how the characteristics of the export destinations determine

¹⁰See, among others, Bastos and Silva (2010) for Portugal; Baldwin and Harrigan (2011), for the United States; Manova and Zhang (2013) for China; Martin (2012) for France; Görg et al. (2010) for Hungary; and Hallak and Sivadasan (2013) for a comparative analysis using data from India, the United States, Chile, and Colombia.

¹¹These findings are also confirmed in a similar setting by Johnson (2012).

within-firm export quality patterns. In doing this, I abstract from technological differences in the production of quality, so that my results solely reflect demand side variations.

This paper is closely related to a recent literature that studies the effects of income distribution on international trade. Choi et al. (2009) pioneered the study of the relationship between income distribution and trade patterns in vertically differentiated products, showing that countries with more similar income distribution have more similar import price distribution. Fajgelbaum et al. (2011) develop a theoretical model with non-homothetic preferences that relates the shape of a country's income distribution and the pattern of trade of vertically differentiated products. In their model, richer countries have a relatively larger home demand for high-quality goods, and tend to specialize in exporting high-quality products. They find that income inequality has an ambiguous effect on the domestic demand for high-quality goods. However, under certain conditions they show that it increases the demand for high-quality products.¹² Although closely related, my paper differs from Fajgelbaum et al. (2011) in that I focus on firm-level patterns, while they focus on the study of country patterns of trade in vertically differentiated products. In my model I allow multi-quality firms with heterogeneous productivity. This feature is not present in Fajgelbaum et al. (2011), and allows me to derive a richer set of implications for firms. Finally, in contrast to Fajgelbaum et al. (2011), I provide empirical evidence for the quality patterns I document in the theoretical model.

A few recent contributions provide empirical evidence for the relationship between importers' level of income inequality and product unit values. The evidence is in general inconclusive. While Bekkers et al. (2012) document a negative relationship between income inequality and unit values for a large set of countries, Flach and Janeba (2013) find a positive relationship between income inequality and unit values for a sample of Brazilian exporters.¹³ Latzer and Mayneris (2012) find evidence of a positive relationship between income inequality and unit values only for the set of rich importers. I contribute to this literature by providing an explanation for the apparently contradictory results. In my model, I show that the effect of income inequality on the demand for high- and low-quality goods varies according to the income of the importing countries. I provide evidence supporting this mechanism, and in contrast to the above-mentioned studies, I use measures of product quality that are not subject to the usual limitations of unit values.

¹²They need to assume that the proportion of the population consuming low-quality products is larger for all income levels. Although similar, this condition is somewhat stronger than imposing positively skewed income distributions, as I do in this paper.

¹³Bekkers et al. (2012) interpret their finding as evidence in favor of hierarchical preferences as opposed to other demand structures. The preferences I use in my model can be seen as a reduced form of hierarchical preferences, with an essential homogeneous good and a luxury, vertically differentiated good that is ranked below the homogeneous good in the list of necessities.

My paper is not the first to use data from the wine industry to study quality patterns in trade. Crozet et al. (2012) use firm-level data from the French Champagne industry to estimate a quality version of Melitz (2003). Using ratings from wine experts as a quality proxy, they document quality sorting of firms into destinations, and a positive relationship between quality and firms' unit values. My paper differs from their analysis in that I focus on the within-firm quality heterogeneity, whereas their study is focused on quality patterns at the firm level. Another closely related contribution is Chen and Juvenal (2014). These authors use information from the Argentinean wine industry to study whether the extent to which firms' price-to-market is exacerbated or lessened for higher-quality goods. Unlike Chen and Juvenal (2014), in this paper I exploit the cross-sectional dispersion of quality, while they use the temporal variation of quality and exchange rate movements to identify the pass-through from exchange rate into prices.

Finally, my paper relates to the literature estimating product quality using trade data. Khandelwal (2010) estimates product quality using U.S. import data. His methodology is based on the insight that within countries exporting a given product (conditional on price) higher-quality goods should have a higher market share.¹⁴ Hallak and Schott (2011) use a similar methodology to derive industry-level quality indexes for a cross-section of countries, while Gervais (2014) and Piveteau and Smagghue (2014) develop a method for recovering firm-level quality. In contrast to this literature, instead of estimating quality I use quality measures in the spirit of Crozet et al. (2012) and Chen and Juvenal (2014).

3 Background and Data

In this section I provide background on the wine industry. Then I describe the main dataset used in the paper. Finally, I show the two main stylized facts that serve as the basis for the theoretical model I present in section 3.

3.1 The Wine Industry

The wine industry has many features that make it particularly well suited for studying quality patterns in international trade. First, the market structure satisfies two important assumptions of monopolistic competition: varieties feature a high degree of product differentiation, and the industry is composed of a large number of relatively small competitors. Second, the vast majority of producers are multi-product firms, and their products display a wide variation in quality. Both elements are important for the theoretical and empirical analysis I perform in this paper. The mo-

¹⁴Operationally, Khandelwal (2010) estimates a nested logit and recover quality for each product-country-year triplet from country-product and year fixed effects.

nopolistic competition assumption is at the core of recent models of international trade, and it is a central piece in the model I present in section 4. In addition, the fact that varieties are not only horizontally but also vertically differentiated is key for the validity of the results in section 6, where I exploit the within-firm quality variation across destinations.

A basic requirement for an industry to be monopolistically competitive is the presence of differentiated products. The wine industry satisfies this assumption: wines are differentiated in various dimensions, and consumers have different preferences for each of these attributes. Perhaps one of the most important differentiating elements is the region of origin of the wine. The *terroir* – the land where the grapes are grown – determines the quality and specific attributes of the wine. Wineries use this information in the commercialization of fine wine, printing the *domain of origin* (D.O.) of the grapes on the labels of fine wine. In addition to the domain of origin, the vintage of the wine – the year in which grapes were harvested – and the wine grape (e.g., Cabernet Sauvignon, Pinot Noir, Merlot) play a relevant differentiating role in wine commercialization. While the vintage of the wine in combination with its domain of origin might be an indication of quality, the wine grape type is an horizontal attribute over which consumers have different preferences.¹⁵ Finally, even within the same *terroir*, vintage, and wine grape, wines may differ in other attributes, such as the degree of astringency, sweetness, aroma, bouquet, and flavor.

A second requirement of monopolistic competition is the presence of a large number of producers participating in the industry. According to Morgan Stanley, in 2013 there were over one million wine producers in the world, being the vast majority small participants relative to the overall size of the industry.¹⁶ While the possibility of large domestic leaders dominating the industry cannot be dismissed, the evidence suggests that producers are typically small compared to the size of the market. Within Chilean wine producers –the sample of wine producers I use in this paper–, the median share over country wine imports is .004%, with the 95th percentile being 2.1%. This suggests that no exporter is large relative to total wine imports, and implies that the amount of market power of individual wineries is most likely limited.

In contrast to other manufacturing industries, wine production features a close connection with upstream activities – grape growing and harvesting. As a result, a vast majority of wineries are vertically integrated over vineyards. There are two main reasons for this. First, the transportation of grapes over long distances is usually not possible without rotting or crushing the grapes. Second, grape-growing conditions strongly determine the attributes of the wine (e.g., flavor, aroma), which makes it advisable for wineries to closely supervise every stage of the grape-growing process.

¹⁵Grape quality crucially depends on the climatic condition in which grapes are grown; thus, the year and region where the grapes are grown affects the quality of the wine.

¹⁶See <http://blogs.reuters.com/counterparties/files/2013/10/Global-Wine-Shortage.pdf>, .

Vertical integration tends to be more common among wineries with a focus on the production of fine wine, while grape acquisition from third parties is more common in the production of table or bulk wine.¹⁷

Finally, I discuss quality differences *within* wineries. Wineries typically produce multiple varieties of wine in different quality segments. This is partially due to the fact that, even within a vineyard, the quality of the grapes might vary significantly. In general, quality differences in the grapes can occur either as a consequence of actions taken by the winemaker during the grape-growing stage, or by the presence of *micro-terroirs*, where grapes grown achieve an unusually high level of quality.¹⁸ In addition, even if similar grapes are used in wine production, the winemaker can arbitrarily improve the wine quality by using inputs of better quality (e.g., ageing the wine in new oak barrels instead of stainless steel tanks) or adapting the production process to the particular chemical properties of the grapes. Thus, while capacity constraints may be relevant for high-end wines (that typically use grapes from very specific *micro-terroirs*), the wine production process offer different possibilities where the wine maker can affect the wine quality. Importantly, when there are differences in the quality of the grapes or must, fermentation and ageing is typically done in different tanks, and the resulting wine packaged under different brand labels. To avoid significant differences in the quality within brand labels, winemakers blend the fermented or aged must from different tanks, so that the wine contained in any pair of bottles of the same brand is very similar.

3.2 Data

The main data I use comes from the Chilean wine industry, which has a long winemaking tradition that goes back to the eighteenth century. Until circa 1980, wine production was performed in a relatively rudimentary way, and the resulting wine was not adequate for exporting due to its low quality standards. Only in the decade of the 1980 Chilean wine production take off, after the introduction of new production techniques and the start of joint ventures between Chilean wineries and foreign wine producers that facilitated technological transference from abroad.¹⁹ Since then, Chile

¹⁷According to information I collected in interviews with Chilean wine producers, mixed regimes – with wineries producing a portion of the grapes and buying the rest from third parties – are also common in the industry and occur in both large- and small-scale wineries.

¹⁸For instance, the practice of pruning vines improves fruit quality, because it allows bunches to receive more nutrients from the soil. In addition, vine-pruning is believed to help the stabilization of production over time, since vines are not stressed in particular years with unusually high or low nutrients.

¹⁹A key technological innovation that allowed for more efficient production was the replacement of wooden vats with stainless steel tanks used for fermentation. The leaders in adopting this production technique were Miguel Torres, a Spanish winery that began producing in Chile in 1981, and Vina Canepa, a traditional Chilean winery. For a more detailed description of the Chilean wine industry in historical perspective, see Agosin and Bravo-Ortega (2009).

has become one of the world's most dynamic wine regions. According to the Food and Agriculture Organization (FAO), Chile was the seventh-largest wine producer in 2010. Wine production in Chile is predominantly export-oriented: less than one-third of total Chilean production is consumed domestically (Wines of Chile, 2010).²⁰ As shown in Figure 1, Chilean wine is exported to practically all countries in America, Europe, and East Asia. Out of the total of 128 destinations where Chilean wine was exported during the period 2005-2010, the main markets for Chilean exports for the period were the United States and Great Britain, followed – with a significant gap – by Canada, the Netherlands, Brazil, Ireland, Denmark, Germany, Japan, and Mexico.

The data I use consists of shipment-level data of Chilean wine exports.²¹ This data is collected by the Chilean Customs Service and processed by Intelvid, a Chilean market intelligence company that provides analytic market intelligence information to Wines of Chile – the main association of Chilean wineries. It covers the universe of wine exports for all shipments made between 2005 and 2010.²² The data is available at a monthly frequency, however, I aggregate it up to the annual level to avoid dealing with seasonal patterns in export shipments. For each shipment, the data contains information on the firm name and tax ID, destination country, FOB value (in U.S. dollars), volume (in liters), and FOB price of the shipment. In addition, the data contains two lines of product attributes, with information on the brand name, the type of merchandise (e.g. "red wine" or "white wine"), wine grape (e.g., Cabernet Sauvignon or Merlot), vintage year, and other complementary information, such as alcoholic graduation, volatile acidity, vintage, and packaging (e.g. bottles of 750 c.c., or boxes of 3 liters).

To avoid comparing wine in different formats (e.g., bulk, bottled, in bags or boxes), I restrict the sample to the subset of bottled wine in containers of less than 2 liters. I also drop the few shipments of sparkling wine (less than 1% of the total FOB value). After these adjustments, the product data can be mapped to the 6-digit HS code "Wine other than sparkling from fresh grapes, including grape must with fermentation prevented or arrested by the addition of alcohol, in containers holding 2 liters or less" (code 2204.21). Table 1 suggests that these choices do not affect the representativeness of the dataset: bottled wine exports comprise around 85% of total exports (column 4), and over 99% of the FOB value reported in COMTRADE for bottled wine (column 5).

²⁰This is in stark contrast to other wine-producing countries, such as the United States, Argentina, China, or Italy, where over 60% of overall production is for domestic consumption (see Wines of Chile, 2010).

²¹In appendix A, I provide a more detailed description of the dataset.

²²The Chilean Customs Service requires all exporters to register the quantity, value, and a detailed description of each shipment valued at US\$2,000 or more. Unlike other customs-level datasets (e.g. countries in the Euro Zone), I observe the value of low-value shipments, although for these there might be less detail regarding the attributes of the exported good.

The trade literature usually defines products in terms of highly disaggregated (8- or 10-digit) HS codes or similar nomenclatures (see Khandelwal, 2010; Hallak and Schott, 2011; Manova and Zhang, 2012, among others). The Chilean data can easily be mapped to 10-digit HS codes using information of the wine grapes as well.²³ However, if such disaggregation is performed, the resulting products would be composed of varieties featuring very different horizontal and vertical attributes. To bypass this issue, I define products in terms of the brand name printed on the label. This ensures that when comparing products across destinations, any variation in the price or value of a given shipment is not due to compositional changes, but to actual changes in the product.²⁴

Sample Selection and Data Consistency

In order to ensure consistent brand categories, I follow three steps. First, I drop observations where no brand name can be identified. Second, I only consider data from firms with exports over US\$250,000 in all years. Third, I drop all exporters corresponding to intermediaries.²⁵ Finally, in order to avoid outliers as well as bulk wine mistakenly classified as bottled wine, I drop all shipment with FOB prices lower than US\$5 or higher than US\$1,000 per case of wine (399 observations).²⁶ The final dataset consists of 422,315 shipments, comprising 131 wineries and 1,334 brands exported to 143 destinations over the period 2005-2010.

3.3 Measure of Wine Quality

A common practice among Chilean wine producers is to include quality appellations on wine labels to signalize the intrinsic wine quality to the consumers. For instance, young, simple wines are differentiated from more complex, aged wines by using the appellation "Reserve" in the label of the latter category. Importantly for my purpose, these appellations are legally regulated in Chile. This alleviates the concern of a spurious relation between the quality appellations printed on the labels and the quality of the wine.

In this paper, I use quality appellations embedded in wine labels as the main measure of quality. In particular, I use following appellations: Varietal, Reserve, Grand Reserve, and Premium (where Varietal is the lowest and Premium is the highest quality). The Varietal appellation is given to

²³Product classifications higher than 6 digits reflects local production and usually differs from country to country. In the case of Chile the disaggregation from 6 to 10 digits enlarges the number of product categories to 31 (see <http://www.aduana.cl/exportaciones/aduana/2007-04-16/165951.html>).

²⁴The data also allows to define products in terms of other attributes, such as winegrape and vintage of the bottle. However, the variation in unit values suggest that these attributes are at least an order of magnitude less relevant than the brand name. Nevertheless, I check the robustness of my findings to more detailed product definitions.

²⁵To classify firms as wine manufacturers I manually verify (1) the website of the exporter (if any), (2) the existence of wine brand associated with the exporter, and (3) whether the exporter was included in the "Vineyards and Wineries of Chile Compendium" Nuevos Mundos (2004)

²⁶Prices are reported in terms of 9-liter cases, which corresponds to 12 bottles of 750 c.c.

young wines, and typically receive no ageing and are released immediately to the market after they are bottled. In contrast, most Reserve wines are aged in oak barrels for over 6-8 months.²⁷ Wineries further differentiate their production lines using the term "Grand Reserve" to indicate Reserve wines of relatively higher quality. Finally, wineries distinguish the best wines in their production line with the appellatives "Icon" or "Premium".²⁸

Quality appellations are subject to two caveats. First, not every wine variety has a quality appellation embedded in its label: out of the total 1,334 varieties, I successfully assign quality categories to 1,206 brands, which represents 98% of the total exports.²⁹ Second self-reported quality measures may be a poor measure of wine quality if wineries choose the denominations only as a marketing tool to charge higher prices. Although this concern cannot be dismissed, the significant reward that the market gives to wines with better appellations suggests that these quality denominations in fact reflect – at least partially – wine quality. Figure 3 illustrates this point, showing the average price for each of the four quality categories, their standard deviation, and the 5th and 95th percentiles of the price distribution. While there is some overlap across quality categories, Figure 3 shows a strong positive relationship between the four quality categories and brand-level average prices, with average prices ranging from US\$21 in Varietal wines to US\$197 in Premium wines for a 12/750-c.c. case. Price dispersion – measured in terms of the standard deviation – also increases with quality, going from 6.0 in varietal wines to 99.7 in premium wines.³⁰

As a robustness check, I also use prices defined at the variety level as a measure of quality. The trade literature traditionally uses unit values calculated over product categories as a quality proxy, based on the belief that higher-quality products are produced in a more costly manner, and that the higher cost is transferred – at least partially – to prices. The fact that varieties within product categories can be clearly identified makes prices less subject to aggregation bias. As I explained in section 3.2, the data allows me to define varieties in terms of the brand name, wine grape, and vintage printed on the label of the wine bottle. This definition coincides with the way in which

²⁷However, the Reserve denomination in Chile does not require ageing either in wood or stain barrels; it only requires "*distinctive organoleptic properties*". See <http://www.winesofchile.org/wp/the-wines/understanding-a-label/> for a detailed explanation on quality appellations as well as other content included in the labels of Chilean wine bottles.

²⁸Grand Reserve wines are typically aged in first- or second-use oak barrels (for 12 to 24 months) and in their bottles for a total ageing period of about 3 years before being released to the market. Icon or Premium wines are produced with the best grapes of the vineyards, selected from specific *micro-terroirs*, and aged in first-use oak barrels only and in bottles for a total of 4-5 years.

²⁹The quality appellations are obtained either directly from the wine label printed on the bottles, or from the wineries website. "Varietal" wines are typically not directly identifiable from wine labels. In these case, I seek for the word "young" and similar in the wine description. In addition, I assign the label Varietal to all wines where the FOB price is less than US\$15 for a case of 12 750-c.c. bottles (equivalent to about US\$5-7 retail price in the U.S.).

³⁰Alternative measures of dispersion – such as the coefficient of variation – show a similar pattern. In the appendix I also show that the quality appellations are positively related to quality rating made by wine experts.

consumers see products when they buy them. Consequently, prices in my sample are a closer quality proxy than they are in studies defining prices as unit values over product categories.³¹

3.4 Varieties, Prices and Quality

This subsection presents evidence on the relevance of considering the variety margin when analyzing firm-level quality flows. I first show the distributions of varieties and number of destinations by firms and varieties. Then, I show evidence that suggests that, even if prices are good measures of quality, computing them over product categories hinders a substantial amount of within-firms variation across markets. Finally, I study the relationship between within-firms price, quality and revenues and show the main stylized fact that motivates the model I present in section 4.

Distribution of Varieties and Destinations

Table 2 illustrates the distribution of the number of varieties by firm, and destinations by firm and by varieties for the year 2007.³² Consistent with the evidence in Bernard et al. (2007) for product categories, the distribution of varieties is positively skewed: while firms export an average of 7.2 varieties, the median number of varieties is only 5 (row 1 in Table 2). This reflects the existence of a fat upper tail: firms in the 75th percentile of the distribution export 23 varieties – about two standard deviations over the mean – and the top firm exports 40 varieties.

Next, I provide descriptive statistics for the number of destinations by firm and varieties (rows 2 and 3 of Table 2). These distributions – as the case of the distribution of varieties – are positively skewed as well, with the mean being considerably higher than the median number of destinations by firm and varieties. Interestingly, a comparison between the distributions of destinations by firms and varieties suggests that the distribution by firms first-order stochastically dominates the distribution of destinations by varieties. A typical product is exported to only half of the markets where the firm is actively exporting, and the number of destinations by products is larger than the number of destinations by varieties for all quartile of the respective distributions. This conclusion is confirmed by Figure 2, which depicts the empirical distributions of destinations by firms and varieties. Since the sum of all destinations covered by the different varieties should add up to the number of destinations covered by firms, this finding implies that the menu of varieties offered by firms to each market varies from country to country. This fact motivates the analysis in the next section, where I study whether the difference in the number of destinations by firm and product is

³¹It is important to stress that while prices in the wine data are less subject to aggregation issues, they might still be reflecting the action of other factors, such as markups. In the data, it is common to see within-firm price differences of tenfold or more between the cheapest and the most expensive products (see Table 2). While markups might contribute to this wedge, it is unlikely that they can fully account for differences of this order of magnitude.

³²Results are not qualitatively different if any other year in the sample is chosen.

systematically correlated with the quality of the products and the characteristics of the markets.

Price Dispersion

Even if prices are good measures of quality, computing them over product categories may hinder a substantial amount of variation within-firms and across markets. To assess the importance of the different margins – firms, destinations and varieties – in overall price dispersion, I run a simple regression of log prices against different sets of fixed effects:

$$\log P_{kijt} = \{\text{Year FE}\} + \{\text{Other FE}\} + \varepsilon_{kijt}$$

where the subscripts (k, i, j, t) denotes varieties, firms, destinations and years. Table 3 shows the R^2 , adjusted R^2 and standard deviation of the residuals from running (1) through OLS. The first row reveals that log prices vary substantially across brands and countries: its standard deviation is 0.85 log points. Rows 2 to 5 analyze the contribution of destinations and firms to log price dispersion. When controlling for country fixed effects, the standard deviation of log prices falls 0.83 log points and the R-squared increases to about 5%, which suggests that only a minor part of the price variation is due to difference in average prices across countries. Rows 3 and 4 analyze the contribution of the firm-product margin, and its interaction with the destination market.³³ Results suggest that the firm-product margin is by far more important than the destination market. However, even when interacted with destinations FE, the firm-product margin accounts for less than half of the overall variation, while the standard deviation of the residuals falls only from 0.83 to 0.65. Finally, I run regression (1) using variety fixed-effects only (row 5). Results suggest that most of the price variation is accounted for by differences in the average price of varieties: after controlling for varieties fixed-effects, the standard deviation of log prices falls to 0.16, while the R-squared increases to about 96%.³⁴ This last margin is precisely the object of study in this paper. By not accounting for this margin, the previous literature significantly underestimates the overall variation in the price of internationally traded products across destinations.

Relation between within-firm price, quality and revenues

Tables 2 and 3 provide general background on the different margins exploited in this paper (firms, destinations, products). However, it says little about which type of products are more important for the firms in terms of revenues. In Tables 4 and 5, I take a step forward in this direction by

³³Results including firm×HS8 fixed effects (not reported) are almost identical to using firm fixed effects only. The reason for this is that the wine dataset include shipments from a single HS6 product category; therefore, the additional fixed effects add little information.

³⁴The residual variation in log prices can be thought of as an indication of the contribution of within-varieties markups variation across destinations. The numbers in this table suggest that product markup accounts for about 19% (0.16/0.85) of the overall dispersion in the price of exports of bottled Chilean wine across destinations.

analyzing whether the revenue share of the varieties increases or decreases with prices and quality. In both Tables, I rank varieties from left to right in terms of sales, with a highest rank being equal to one. Table 4 shows the relation with prices, and ranks varieties from top to bottom in terms of price. Table 5 repeats this exercise using instead the quality segments discussed in 3.3. These Tables only considers firms producing at least five products in this table, which implies that the total number of products ranked first to fifth should be identical (see column and row *Total*).

Table 4 reveals that the top-selling variety rarely coincide with the most expensive products of a firm. In over three-quarters (5.9/8.0) of the firms, the top-selling variety (in terms of revenues) is ranked 5 or below in terms of price, and in only 14% of the firms the best-selling variety is ranked first, second or third (see first column). Similarly, the first row of Table 4 reveals that the most expensive variety of a firm is rarely ranked between the best-selling varieties: it is ranked fifth or below in terms of export revenues in about 80% of the firms. Table 5 confirms these patterns using appellations as quality proxies.³⁵ In about 55% of firms, the best-selling variety corresponds to Varietal wines (the lowest quality appellation), while in only 7% firms the best-selling variety is a premium wine. Tables A.1 and A.2 in the appendix shows that these patterns does not hold when products are defined at the more aggregate level (either at the HS6-level or HS8-level):³⁶ in about one-third of the firms the best-selling variety is ranked first, second or third, and revenue shares does not show a negative relation with unit-value ranking.³⁷

The fact that each variety's revenue share decreases with price is hard to reconcile with quality-based trade models with representative consumers. In these models, quality is modeled as a preference parameter that increases product appeal. Under common parameterizations, these models imply that product quality increases both revenues and prices, contradicting the finding I document in this paper (e.g. Baldwin and Harrigan, 2011; Kugler and Verhoogen, 2012, among others).³⁸ In this paper I explore a different mechanism that does not relies on specific assumptions on the sensitivity of cost to product quality to explain the pattern. I argue that the previous literature, by abstracting from consumer heterogeneity, fail to capture a key element of quality demand: dif-

³⁵This is not too surprising – Figure 3 shows that prices and quality are positively correlated –.

³⁶Unit values are expressed in log-deviations from the average log unit value of the product category. Products are expressed in homogeneous units within product categories. Thus, unit values log-deviations from the mean are directly comparable.

³⁷My results for aggregated product categories are somewhat weaker than the findings in Manova and Zhang (2013). Using a Chinese dataset for manufacturing firms, they show that top-selling varieties tend to be the most expensive articles of the firms. I attribute the discrepancy to the fact that they compare firms producing various number of products (e.g., in their results the number of total products ranked first is lower than the number ranked second)

³⁸In principle, revenues may increase or decrease with quality, depending on the sensitivity of marginal costs and product valuation with respect to quality. However, as Khandelwal (2010), and Antoniadis (2013) show, for products with a large scope for quality differentiation – such as wine –, both revenues and prices increase with product quality, contradicting the finding I document in this paper.

ferent individuals may optimally choose to consume different quality levels, depending on their income level. When individuals buy cars, they usually buy the best model that they can afford given their resources: if they are looking for a compact car, they either buy a BMW i3 or a Honda Fit, but not both (or a continuum of cars of different qualities).³⁹ This is also true in other industries, such as wine: Sophisticated rich consumers do not buy cheap wine packed in bags, nor do less affluent consumers buy \$100 bottles. This implies that it is not merely average income, but the entire distribution of income that matter for trade. I use this as the main motivation for my theoretical model, where consumer's heterogeneity plays a predominant role. This mechanism has the advantage that does not relies on specific assumptions on the sensitivity of cost to product quality. This simple modification has important implications for the within-firm trade patterns of quality across countries that I explore later on.

4 Model

In this section, I develop a simple framework to study the factors driving firms' quality mix across export destinations. The model builds on Fajgelbaum et al. (2011) insights on trade in vertically differentiated products. Differently from them, I enrich firm's environment by allowing firms to be heterogeneous in their efficiency levels and produce in multiple quality segments. This allows me to study how the average quality shipped varies across firms, and how it is affected by demand variations originated by differences in the characteristics of the importing countries.

The world is composed by I asymmetric countries trading with each other. Hereafter, the exporting country is represented by the subscript i , and the importing country by j . Consumers are endowed with different amounts of effective labor, which is supplied inelastically to firms at the market wage rate. Firms use labor as the only production factor, and they are heterogeneous in their productivity. Countries may differ in their size and distribution of labor endowments, but they share the same preferences and productivity distribution.

In each country, there are two industries: a homogeneous-good sector, and a sector producing varieties of a differentiated product. The homogeneous sector is perfectly competitive, produces a good that is consumed domestically under constant returns to scale and produced by all countries. I use this good as the numeraire and normalize its price to one in all countries. Since labor is only production factor, this normalization implies a unit wage rate per unit of effective labor. In contrast, the differentiated product sector is composed of a continuum of monopolistic competitors, each of whom produces a differentiated variety. Varieties are traded internationally, and may differ in their

³⁹The manufacturer's suggested retail price (MSRP) for a BMW i3 is in the range \$41,350-\$45,200, while the MSRP for a Honda Fit is \$15,525-\$20,800 depending on the amenities included.

horizontal attributes (e.g., shape, color, etc.), as well as in their vertical attributes (e.g, quality). While there is a continuum of horizontal attributes in which products may differ, I assume that there are only two quality levels: high (H) and low (L).

4.1 Preferences and Demand

Consumers derive utility from the homogeneous good (z) and the varieties consumed in the differentiated good sector. The homogeneous good can be consumed in any amount. However, the differentiated varieties come in the form of composites of different qualities, and can only be consumed as a whole.⁴⁰ This implies that the consumption of the differentiated good – and not the amount of it consumed – is what gives utility to the consumer.⁴¹ I follow Flach and Janeba (2013) in specifying the following functional form for consumers' preferences:

$$U_j = z \cdot q \tag{1}$$

with

$$q = \begin{cases} q_H, & \text{if } q = H \\ q_L, & \text{if } q = L \\ 1, & \text{otherwise.} \end{cases} \tag{2}$$

where $q_H > q_L > 1$, and $\{q_H, q_L\}$ are parameters translating quality into utility units. The consumer optimizes choosing the quality of the differentiated good, and the amount of the homogeneous good to be consumed. If he chooses quality $q \in \{H, L\}$, he consumes one unit of a CES composite of horizontally differentiated varieties with price P_j^q , and spends the remainder of his income in the homogeneous good.⁴² The elasticity of substitution in both quality segments is σ . While it may be possible to argue that high-quality consumers are less sensitive to prices as in Fajgelbaum et al. (2011), I avoid introducing such differences to focus on the effect of income

⁴⁰In the model, quality is represented as a utility function parameter, and is defined in terms of average utility per unit of homogeneous good consumption. This implies that, conditional on the level of homogeneous good consumption, a product will have higher quality if all consumers prefer the same (higher-quality) product when the products are offered at the same price. Thus, it involves any feature – either subjective or objective-changing the appeal of two *ex ante* identical products to the consumer. My definition of quality is reminiscent of Sutton (1986), where the main difference is the fact that I not only condition on price, but also on the level of homogenous good consumption.

⁴¹This assumption is common in models of product quality with non-homothetic preferences. See Flam and Helpman (1987); Fajgelbaum et al. (2011); Flach and Janeba (2013), among others.

⁴²Note that the fact that individuals are restricted to consume at most one unit of the differentiated composite does not imply that a discrete consumption of the individual varieties composing the composite.

distribution.⁴³

The utility function (1) features a few interesting properties. First, the homogeneous good and the quality of the differentiated good are complementary in consumption. This feature, – which is common to related models of vertical differentiation (see Flam and Helpman, 1987; Fajgelbaum et al., 2011, among others) – implies that the marginal value of quality is higher for richer consumers and is useful in generating non-homothetic aggregate demands. Second, consuming the differentiated good only delivers strictly positive utility if some of the homogeneous good is already consumed. Thus, some consumers may choose to consume none of the differentiated good. Finally, no consumer optimally chooses to consume both qualities, since the consumption of both quality levels delivers strictly less utility than consuming none of them.⁴⁴

The consumer’s problem consists of finding the amount of the homogeneous good and quality of the differentiated good that maximizes (1) subject to the consumer’s budget constraint. Since the consumer buys at most one unit of the differentiated good, the solution to the problem can be found by comparing the utility of three alternatives: (i) consume only the homogeneous good and none of the differentiated good; (ii) consume low quality and the homogeneous good; and (iii) consume high quality and the homogeneous good. The structure of the preferences implies that the solution to this problem is characterized by two income thresholds y_j^L and y_j^H , which determine the quality choice and amount of the homogeneous good to be consumed as a function of the consumer’s income y .⁴⁵ Denoting by P_j^q the price of the CES composite of quality $q = \{H, L\}$ in country j , it can be shown that the solution to the consumer’s problem is:

$$\begin{aligned} z &= y; \quad \mathbb{I}(q=L) = 0; \quad \mathbb{I}(q=H) = 0 & \text{if } y < y_j^L \\ z &= y - P_j^L; \quad \mathbb{I}(q=L) = 1; \quad \mathbb{I}(q=H) = 0 & \text{if } y_j^L \leq y < y_j^H \\ z &= y - P_j^H; \quad \mathbb{I}(q=L) = 0; \quad \mathbb{I}(q=H) = 1 & \text{if } y \geq y_j^H \end{aligned} \quad (3)$$

where $\mathbb{I}(\cdot)$ is an indicator function equal to one if quality q is consumed and zero otherwise, $y_j^L = \frac{P_j^L q_L}{q_L - 1}$, $y_j^H = \frac{P_j^H q_H - P_j^L q_L}{q_H - q_L}$, and P_j^q is the price of the composite of quality q in country j . As can be seen in (3), the solution to the consumer’s problem displays quality sorting across individuals: the poorest consumers consume none of the differentiated good, middle-income consumers buy low

⁴³In Section 5 I discuss how the main predictions of the model are affected by this assumption.

⁴⁴With strictly positive prices, consuming both qualities yields less utility than consuming only one quality level, because it reduces the consumption of the homogeneous good, and the second quality consumed does not provide additional utility. In general equilibrium non-positive prices are unfeasible, because it would imply an infinite excess of demand for the underlying varieties.

⁴⁵In this model, consumer’s income is equal to the sum of labor income and dividends derived from firm profits. Thus, consumer’s income y and labor endowments \tilde{y} do not generally coincide.

quality, and the relatively richer consumers buy high quality as well as some of the homogeneous good.⁴⁶

The underlying individual's demand for the horizontally differentiated varieties follows from minimizing the total cost of one unit of the CES composite of each quality. Aggregate demands ($x_{ij}^q(\omega)$) for variety ω produced in country i and consumed in j can then be found by summing individual demands over the country's population consuming quality q . Since the only source of consumer heterogeneity is differences in the labor endowments, which I assume are distributed according to the c.d.f. $M_j(\cdot)$, aggregate demands can be written as:

$$x_{ij}^q(\omega) = \left(\frac{p_{ij}^H(\omega)}{P_j^H} \right)^{-\sigma} \int_{y_j^H}^{\infty} dM_j(y) \cdot N_j \quad (4)$$

where $p_{ij}^q(\omega)$ denotes the price of variety ω of quality q , N_j is population size of country j , y is consumer's income (which equals labor income plus dividends revenue), and $P_j^q = [\int_{\omega} p_{ij}^q(\omega)^{1-\sigma} d\omega]^{\frac{1}{1-\sigma}}$ is the CES aggregate price of the composite.⁴⁷

4.2 Production

In each country's differentiated sector, there is a continuum of firms producing varieties of a product. Following Chaney (2008), I assume that firms' productivity φ in each country are drawn from a Pareto distribution, defined over the interval $[1, \infty)$, with cdf $G(\varphi) = 1 - \varphi^{-k}$. I follow the usual assumption that $k > \sigma - 1$ to ensure a finite size distribution. In each country there is an exogenously given set of potential entrants, which for simplicity I assume is proportional to population.⁴⁸ Since I restrict entry, in this model firms generate net profits. To accommodate this fact, I assume as in Chaney (2008) that world profits are collected and redistributed equally across all workers, each of whom owns one share of a diversified global fund. Thus, for each consumer, income (y) is equal to the sum of labor income (\tilde{y}) plus dividends (ν).

Firms in the differentiated sector may operate in one or two quality segments using labor as only production factor. The marginal cost of producing a variety with quality q is equal to a constant

⁴⁶As (3) makes clear, in the model 'rich' and 'poor' customers are defined not only as a function of income, but also of prices. I rule out the case where relatively rich consumers prefer low to high quality by assuming that $y_j^H > y_j^L$, which can be achieved by imposing $\frac{P_j^H}{P_j^L} > \frac{(q_H-1)}{q_H} \frac{q_L}{(q_L-1)}$.

⁴⁷There is a slight abuse of notation in using ω for denoting high- and low-quality varieties. Varieties are defined in terms of both horizontal and vertical attributes and therefore, do not need to be the same for high and low quality.

⁴⁸This assumption is made for analytical simplicity and is not critical for the main quantitative implications of the model. In a more general setting, Arkolakis et al. (2008) and Arkolakis et al. (2012) show that models with free entry deliver similar expressions for aggregate trade flows and gains from trade to models with a fixed set of potential entrants, as the one I develop in this paper.

c_q times the unit labor requirement $1/\varphi$. I assume that producing high quality is more costly than producing low quality: $c_H > c_L$. This reflects the idea that producing high quality requires more workers (or workers of higher quality, as in Kugler and Verhoogen, 2012). For analytical simplicity, I abstract from the firm's product scope decision and assume that firms can produce at most one variety in each quality segment. Since the aim of the model is to understand how the relative quality of firms' exports varies across destinations, this simplification is immaterial for the main implications of the model.

Firms from country i seeking to sell in country j bear two types of trade costs. First, there is a variable iceberg-type transportation cost: $\tau_{ij} \geq 1$ units of the good have to be shipped for one unit to arrive (with $\tau_{ii} = 1$). In addition, serving any country j involves the payment of a product-specific fixed cost F_{ij} , which is paid in units of the homogeneous good. Thus, if a firm enters a market simultaneously in both quality segments, it has to pay the entry cost twice – once for each product. This reflects the idea that reaching customers is costly (Arkolakis, 2010), and since in the model no consumer simultaneously purchases high and low quality, the customer network developed by a firm in a given quality segment has no value for offering a different quality. Instead, firms need to develop a new customer network for offering their products in a different segment.⁴⁹

Firm's Problem

The problem of the firm consists of finding the price in each quality segment that maximizes profits, taking as given the aggregate demand (4) for high and low quality:

$$\max_{\{p\}} \pi_{ij}^q(\omega) = \left[p - c_q \frac{\tau_{ij}}{\varphi} \right] \left[\frac{p}{P_j^q} \right]^{-\sigma} Y_j^q \cdot N_j - F_{ij} \quad (5)$$

where $Y_j^H = \int_{y_j^H}^{\infty} dM_j(y)$ and $Y_j^L = \int_{y_j^L}^{y_j^H} dM_j(y)$, with y_j^L and y_j^H being defined in (3). Given the CES structure, in each quality segment optimal prices are a constant markup over marginal cost:

$$p_{ij}^H(\varphi) = \left(\frac{\sigma}{\sigma - 1} \right) \frac{c_H \tau_{ij}}{\varphi} \quad \text{and} \quad p_{ij}^L(\varphi) = \left(\frac{\sigma}{\sigma - 1} \right) \frac{c_L \tau_{ij}}{\varphi} \quad (6)$$

As can be seen in (6), conditional on productivity firms charge a higher price for high quality in each destination. Since markups are the same for both qualities, all price differences within firm-product-destination are accounted for by the higher marginal cost in the high-quality segment.⁵⁰

⁴⁹Anecdotal evidence on this type of fixed costs can be found in many industries. For instance, in the wine industry, wineries typically offer premium high-quality wines primarily on-premise in restaurants and hotels, and offer relatively low-quality wines off-premise using the distribution networks of supermarkets and stores.

⁵⁰A second reason for which prices may be higher in the high quality segment are differences in markups. As

Firm profits are obtained replacing (6) in (5):

$$\pi_{ij}^q(\varphi) = \frac{(P_j^q)^\sigma}{\sigma} \left[\frac{\sigma}{\sigma-1} \cdot \frac{c_q \tau_{ij}}{\varphi} \right]^{1-\sigma} \cdot Y_j^q \cdot N_j - F_{ij} \quad (7)$$

4.3 Firm Entry

In this model, not every firm exports, nor every exporting firm export to every destination. Firms only stay in markets where they can obtain enough variable profits to cover the per-product fixed entry cost. Since profits increase monotonically with productivity φ , firms' entry decision can be characterized by a threshold rule: firms with productivity above market j 's threshold productivity $\tilde{\varphi}_{ij}^q$ make non-negative profits selling quality q , while the remaining firms exit immediately after observing their productivity draw. The productivity thresholds for country i 's firms serving market j in quality segment $q \in \{H, L\}$ is defined by the following expression:

$$\pi_{ij}^q(\tilde{\varphi}_{ij}^q) = 0 : \quad \tilde{\varphi}_{ij}^q = \gamma_1 \left[\frac{(P_j^q)^{-\sigma} F_{ij}}{Y_j^q \cdot N_j} \right]^{\frac{1}{\sigma-1}} c_q \tau_{ij} \quad (8)$$

where $\gamma_1 = (\sigma/(\sigma-1)) \cdot \sigma^{1/(\sigma-1)}$ is a constant that depends negatively on the elasticity of substitution σ . The value of the productivity thresholds is determined by trade costs τ_{ij} and F_{ij} ; country size N_j ; customers density Y_j^q ; and CES composite's price P_j^q . While fixed and variable trade costs are exogenous in the model, customers density Y_j^q and composite price P_j^q are equilibrium objects that need to be determined.⁵¹ Fortunately, under the assumptions of fixed entry and Pareto distribution for productivity, the equilibrium CES aggregate price can be solved analytically as a function of trade costs and the mass of customers in each country and quality level:⁵²

$$P_j^q = \gamma_3 \times c_q^{\frac{k(\sigma-1)}{\lambda}} \times [Y_j^q N_j]^{(\sigma-1-k)/\lambda} \times \theta_j \quad (9)$$

Fajgelbaum et al. (2011) argue, high-quality products exhibit a more ample set of characteristics, which enlarge the scope for product differentiation relative to low-quality varieties.

⁵¹Since the notion of equilibrium in my model is similar to Chaney (2008), I avoid trivial repetition and save the full definition of the competitive equilibrium in appendix B for the interested reader.

⁵²Note that the dependence of aggregate price on the mass of customers makes unfeasible to obtain an analytical solution for P_j^q , because it appears in the integrals that defines Y_j^q . However, since Y_j^q monotonically decreases with P_j^q , equation (9) uniquely characterizes the equilibrium price for each quality segment. In appendix C I provide a detailed derivation of (9).

where $\theta_j = \left[\sum_{i=1}^I N_i \times \tau_{ij}^{-k} \times F_{ij}^{-\left(\frac{k}{\sigma-1}-1\right)} \right]^{\frac{1-\sigma}{\lambda}}$, and λ and γ_3 are constants.⁵³ As in Chaney (2008), θ_j is interpreted as an index of remoteness of country j from the rest of the world and is a weighted average of trade costs incurred by firms exporting to country j . Finally, the equilibrium productivity threshold is found by replacing the price index into (8):

$$\tilde{\varphi}_{ij}^q = \gamma_4 \times \tau_{ij} \times [F_{ij}(\theta_j)^{-\sigma}]^{\frac{1}{\sigma-1}} \times [c_q \cdot Y_j^q \cdot N_j]^{-\frac{(\sigma-1)}{\lambda}} \quad (10)$$

where $\gamma_4 = [\gamma_1 \times (\gamma_3)^{-\sigma/(\sigma-1)}]$.

Equation (10) provides a benchmark for studying firm entry to each market and quality segment. All firms with productivity above the threshold (10) enter market j with quality q , while firms with productivity below that threshold stay out of the market. Two factors affect this threshold across destinations: trade costs and the mass of consumers that are willing to pay for the consumption of each quality. In particular, higher fixed and variable trade costs, and a smaller mass of potential customers reduce the profitability of entering a specific destination making entrance less likely.⁵⁴ Since these elements vary across markets, exporting firm will not generally be active in every markets.

High vs. low quality export entry

The productivity threshold does not only vary across destinations, but also – within importing-exporting country pairs – across quality segments. Two forces determines the relationship between the productivity thresholds. On one hand, entry tends to be more easier in the high-quality segment, because the productivity advantage is less important in terms of price. This leads to a relatively lower threshold in this segment. On the other hand, entry is easier in the quality segments where the density of potential customers is larger –see the last term in square brackets in (10)–. Thus, if the density of individuals consuming low-quality is high enough, it may be possible that the productivity threshold is actually lower in the low-quality segment. As a result, the relationship between high and low-quality thresholds within destinations cannot be determined a priori.

Despite of the inconclusive relationship within destinations for the high- and low-productivity thresholds, the model predicts that across destinations, the thresholds are univocally related to the density of potential customers in each quality segment.⁵⁵ More precisely, in countries with a large

⁵³More precisely, $\lambda = k\sigma - (\sigma - 1)$ and $\gamma_3 = [\gamma_2 \times (\gamma_1)^{\sigma-k-1}]^{-(\sigma-1)/\lambda}$, with $\gamma_2 = \left[\frac{k}{k-(\sigma-1)} \right] \left[\frac{\sigma-1}{\sigma} \right]^{\sigma-1}$.

⁵⁴In contrast to fixed and variable costs, remoteness reduces the productivity threshold. For given trade costs, the profitability of a destination increases with θ_j^q , because entry of firms from the rest of the world is lower, which increases the fraction of the total population served by each successful entrant.

⁵⁵To see this, note that Y_j^q is the only element in (10) varying across quality segments and destinations. Indeed, taking the ratio of (10) for high and low quality we obtain $\tilde{\varphi}_{ij}^H / \tilde{\varphi}_{ij}^L = (Y_j^L / Y_j^H)^{(\sigma-1)/\lambda}$.

market for low (high) quality, the productivity threshold is lower and revenues are higher in the low (high) quality segment upon entry. For instance, in certain poor destinations, it may be possible that entry is only profitable in the high-quality segment –if the country is highly unequal, with a very small middle class.⁵⁶

The fact that productivity thresholds vary across quality segments, implies that aggregate quality content of exports may vary with trade liberalization differently depending on the income distribution of the liberalizing country. For instance, if a country with a relatively large low-quality local market liberalizes (such as China), then the quality of a nation’s exports may decline. In contrast, if liberalization experienced in countries with relatively large high-quality markets –such as Japan– may improve the average quality of exports.

I end this section by briefly discussing how the implications of the model for firm entry across quality segments and destinations differ from the previous literature. In the model, the relative attractiveness of each quality segment across destinations is directly related to the size of the relevant quality market. This feature is a direct consequence of introducing non-homothetic preferences and heterogeneous consumers’ income in an otherwise, standard model of trade with heterogeneous firms. In contrast to my theory, in alternative quality models with homothetic preferences and representative consumers, quality is only driven by the aggregate values of per capita income and market size, but not by the distribution of income (see models based in the quality interpretation of Melitz, 2003, such as Baldwin and Harrigan, 2011; and Kugler and Verhoogen, 2012). Thus, the income distribution channel may help to account why idiosyncratic demand shocks play an important role in determining export outcomes (see Eaton, Kortum, and Kramarz, 2011). In the next section I study in detail the predictions of the model with respect to the characteristics of the importing countries, and discuss the main differences with the preceding literature.

5 Importers Characteristics and Product Quality

In this section I present the model’s predictions regarding firms’s quality decisions across destination countries. I first discuss the role of importing countries’ size and per capita income on the revenues and profits of firms producing differentiated varieties. I then turn the attention to the role the income distribution of the destination countries on within-firm quality patterns.

To derive these predictions, I make the following distributional assumption on countries’ in-

⁵⁶These conclusions, of course, may need to be qualified if markups are allowed to vary endogenously as in Melitz and Ottaviano (2008). In such case, markups decrease as the size of the local quality markets increases. A similar conclusion may be achieved if the instead of imposing homogeneous fixed entry costs across quality segments, I assume that fixed costs reflect marketing costs resulting from the need of contacting local customers as in Arkolakis (2010).

come distribution:

Assumption 1. *Individual endowments are drawn from a Pareto distribution with shape parameter $\alpha_j > 1$, and distributed over $[x_j, \infty)$ according to the c.d.f.*

$$P(y < Y) \equiv H_j(y) = 1 - \left(\frac{x_j}{y}\right)^{\alpha_j} \quad (11)$$

Assumption 1 allows me to study in an analytically convenient way the impact of income inequality on quality patterns. As discussed in Cowell (2011), an attractive feature of the Pareto distribution is that its parameters can be mapped in a straightforward way to per capita income and to different measures of income inequality. Thus, the effect of income per capital and income dispersion on product quality can simply be studied by deriving comparative statistics with respect to the location (x_j) and shape (α_j) characterizing the Pareto distribution. For instance, consider the income mean ϕ_j , which is equal to $\phi_j \equiv \mathbb{E}_j[y] = \frac{\alpha_j}{(\alpha_j-1)}x_j$. Thus, for a given value of the shape parameter α_j , the average income across countries reflects variation in the location parameter x_j . Similarly, it can be shown that the shape parameter α_j , which controls the dispersion of the distribution, is inversely related to a wide array of income inequality measures.⁵⁷ While in this section I use these properties for deriving comparative statistics, later in the empirical section I use these properties to estimate the parameters (α_j, x_j) using per capita income and the Gini index – a measure of income inequality – for a sample of 104 countries.⁵⁸

5.1 Country Size

I first study the relationship between country size, firm’s revenues, and within-firm quality allocation. Intuitively, market size operates through two opposing channels. First, it increases profits because the markup over marginal cost is earned over more consumers. Second, there is a general equilibrium effect that tends to decrease firm’s profits: a larger market size implies a larger number of firms and a lower aggregate price, which reduces demand conditional on productivity. In the following proposition I show that the first effect dominates, implying that sales and profits increase with market size.

⁵⁷Lower values of α_j are related to a more disperse income distribution. See section 4.3 in Cowell (2011) for a good summary of the correspondence between Pareto’s shape parameter and commonly used measures of inequality, such as the Gini index, Theil index, or Atkinson index.

⁵⁸Despite recent criticism, the Pareto distribution has historically proved to be a good approximation of the upper tail of the income distribution (for recent evidence for Germany, United States and United Kingdom, see Clementi and Gallegati, 2005). Given that the mechanism of this paper relies on the density of relatively rich consumers – the poorest individuals does not consume differentiated goods –, using this distribution in the current setting is less problematic than in other contexts.

Proposition 1. *Consider two countries j and k identical in all aspects but size. If country j is larger than k ($N_j > N_k$), and the relative price gap between high- and low-quality (P_j^H / P_j^L) is larger than a constant $\chi > 1$, firm's revenues and profits are higher in destination j for all quality segments.*

Proof. See appendix. □

Since the probability of starting to export to a given country depends on whether firms can make enough variable profits to cover the fixed entry costs, proposition 1 implies that export entry is relatively more profitable in larger countries. To gain intuition on this result, assume for the moment that the income thresholds are fixed and do not vary with country size (the proposition is solved considering the endogeneous response of income thresholds induced by the change in prices). Since the shape of the income distribution does not change with country size N_j , the increase in market size is proportionally translated into more consumers for both quality segments, which increases demand and entry gains, just as in Melitz (2003).⁵⁹ This conclusion holds as well when the effect of market size on income thresholds is considered. In larger markets – ceteris paribus – aggregate prices and income thresholds are lower, which reinforces the mechanism explained above. Thus, in larger markets the mass of customers consuming high *and* low quality products is larger, and as a consequence, revenues and profits are higher.

5.2 Per Capita Income

After establishing the effect of country size on profits and firm entry, the next step is to find the effect of average income on the within-firm quality allocation across destinations. Per capita income can increase either because the dispersion increases (higher α_j), or if – conditional on a given dispersion – the entire distribution shifts towards higher values of income (higher x_j). Since I want to separately study the effect of per capita income and income dispersion, in this section I identify changes in per capita income with changes in x_j for given values of α_j . Under this assumption, a given percentage change in the location parameter ($\tilde{x}_j = \Delta x_j / x_j$) is exactly translated into a proportional change in per capita income: $\tilde{x}_j = \tilde{\phi}_j$.

When income is distributed Pareto, the fraction of customers buying high and low quality is

⁵⁹Note that the validity of proposition 1 may change if markups are affected negatively by country size as in Melitz and Ottaviano (2008).

given by:

$$Y_j^H = \alpha_j \int_{y_j^H}^{\infty} \frac{x_j^{\alpha_j}}{y^{\alpha_j+1}} dy = \left(\frac{x_j}{y_j^H} \right)^{\alpha_j} \quad (12)$$

$$Y_j^L = \alpha_j \int_{y_j^L}^{y_j^H} \frac{x_j^{\alpha_j}}{y^{\alpha_j+1}} dy = (x_j)^{\alpha_j} \left[\frac{1}{(y_j^L)^{\alpha_j}} - \frac{1}{(y_j^H)^{\alpha_j}} \right] \quad (13)$$

As can be seen, the first order effect – ignoring the effect on income thresholds – of an increase in x_j is to increase both the mass of consumers buying high and low quality. On one side, consumers that previously were consuming just the homogeneous good, begin purchasing the low-quality differentiated composite as they get richer. On the other side, middle-income consumers switch from consuming low- to high-quality. Although in general, it may be possible a reduction of the mass of consumers purchasing low-quality goods, the shape of the Pareto distribution ensures that the mass of marginal consumers that start consuming low quality is larger than the mass switching from low to high-quality, so that revenues in both, high and low-quality segments are higher in richer countries. This also increases the exporting probability, through a reduction in the productivity thresholds.

I formalize the previous discussion in the following proposition:

Proposition 2. *Consider two countries j and k identical in all aspects but per capita income. For a given α_j , if per capita income is higher in country j than in k ($x_j > x_k$), and $P_j^H/P_j^L > \chi > 1$, firm's revenues and profits are higher in destination j for all quality segments.*

Proof. See Appendix. □

In words, proposition 2 suggest that firms have higher incentive to export both high- and low-quality goods to rich countries, because revenues are higher in these countries. Since variable variable profits increase monotonically with revenues with CES demands, the probability of exporting to richer countries is higher, because the productivity thresholds for entering to these countries are lower..

5.3 Income Dispersion

In doing this I make use of the following intermediate lemma.

Lemma 1. *Consider two countries j and k identical in all aspects but income distribution. If their distributions are such that the relative mass of individuals consuming high quality is higher in country j ($Y_j^H/Y_j^L > Y_k^H/Y_k^L$), then firm profits in the high-quality segment are relatively higher*

in country j than in country k , and the relative productivity threshold for high quality in country j is lower than in country k .

Proof. See Appendix □

Lemma 1 can be seen as an extension of proposition 1, and states that firm profits in a given quality segment are relatively higher in countries where there are relatively more consumers demanding products of that quality. The lemma also implies that export entry to the high- (low-) quality segment is more likely in countries where there are relatively more individuals consuming high (low) quality. Although straightforward, this lemma allows me to save an important amount of algebraic derivations and to focus on the intuition behind the results that follow.

Finally, proposition 3 summarizes the effect of income inequality on the within-firm quality composition of exports across destinations:

Proposition 3. *Consider two countries j and k identical in all aspects but income distribution. If country j has higher income inequality than k ($\alpha_j < \alpha_k$), (i) the ratio of firm profits in the high-quality segment relative to the low-quality segment is higher in country j than in k , (ii) the relative productivity threshold for high quality in country j is lower than in country k , and (iii) the intensity of the effect described in (i) is inversely proportional to the level of income of the countries.*

Proof. See Appendix □

Proposition 3 is the main result of this paper and establishes that in countries with high income inequality firms' entry is easier into the high-quality segment. Interestingly, the proposition predicts that the effect of income inequality is nonlinear: in relatively poor countries, firms' incentives to ship high-quality varieties are higher because in these countries firm entry is less likely in all quality segments (see proposition 2).

Although proposition 3 is established for the particular case of Pareto distribution of income, the underlying mechanism is general and can be applied to generic distributions. The result in proposition 3 is driven by the fact that when income dispersion increases, a fraction of the population that was originally consuming low quality can now afford high quality under the new distribution. This implies that the market share captured by high-quality products increases with inequality, while the market share of low-quality products decreases with inequality. Thus, the relative profits of high quality increases, which incentivizes firm entry into the high-quality segment relative to low quality.

5.4 Sensitivity to Alternative Assumptions

A related question raised by propositions 1 and 2 is whether the effect of size and per capita income is stronger in the high- or low-quality segment. In general, if there are no differences in the elasticity of substitution of high and low-quality varieties, revenues increase in the same proportion in both quality segment with destination country's size and income. However, when the elasticity of substitution is lower in the high quality segment, (i) the mass of consumers tend to increase relatively more in the high quality segment, but (ii) aggregate prices fall by more in the high-quality segment (through higher firm entry into that segment). Thus, the aggregate effect is undetermined.

6 Empirics

In this section I return to the data and describe the empirical strategy I follow to test the predictions of the model presented in the previous section. I first describe the different proxies for quality and the measures of income inequality. Later, I discuss the main specifications and identification assumptions of the empirical results. Finally, I discuss the strategy for testing the main predictions of the model in the data.

6.1 Income Distribution

The main empirical prediction of the model relates to the allocation of quality across destinations, and the density of consumers that can afford each quality. According to the model, within countries, very poor individuals consume none of the differentiated good, middle-income individuals consume low-quality varieties, and relatively rich individuals consume high-quality varieties. The proportion of consumers in each quality category may be proxied with available measures of income inequality. However, it is unclear whether such measures capture the variation that is consistent with the main mechanism of the model. For instance, one of the most popular measures of income inequality, the Gini coefficient, is known for assigning low weight to observations in the tail of the distributions (see Cowell and Victoria-Feser, 1996). Since the mechanism of the model relies on the relative share of rich consumers, the Gini coefficient will likely be a poor approximation of the relevant cross-country variation of income inequality.

The first step for deriving the share of the population consuming high and low quality is to estimate the income distribution of the countries importing Chilean wine. Instead of trying to find the best functional for each country, I fix the distribution for all countries and calibrate it to the data

to find the values of the parameters that better characterize income distribution in each country.⁶⁰ The Pareto distribution is the theoretically consistent distribution with my model. However, there is extensive evidence suggesting that this distribution is only a good description of the upper tail of the income distribution. For that reason, I use the lognormal distribution as the benchmark in my empirical analysis and use the Pareto distribution as a robustness check only. Although the lognormal distribution is a poorer approximation than Pareto for describing the density of very rich consumers, it has a better overall fit to the entire income distribution.

An attractive feature of the Pareto and lognormal distributions is that they allow for describing in a parsimonious way the distribution of income. Indeed, each distribution is characterized by only two parameters: shape (α_j) and location (x_j), in the case of Pareto, and mean (μ_j) and standard deviation in the case of the lognormal distribution. Moreover, these parameters can easily be recovered using information of per capita income (\hat{y}_j) and the Gini index (Λ_j) of each country j as

$$[\text{Pareto}] \quad : \quad \alpha_j = \frac{1 + \Lambda_j}{2\Lambda_j} \quad \text{and} \quad x_j = \left[1 - \frac{1}{\alpha_j}\right] \hat{y}_j \quad (14)$$

$$[\text{lognormal}] : \quad \sigma_j = \sqrt{2}\Phi^{-1}\left(\frac{1 + \Lambda_j}{2}\right) \quad \text{and} \quad \mu_j = \ln \hat{y}_j - \frac{1}{2}\sigma_j \quad (15)$$

where $\Phi^{-1}(\cdot)$ denotes the inverse cumulative standard normal distribution function (see Aichison and Brown, 1996; Chotikapanich et al., 1997; Cowell, 2011). To compute the four parameters in (14) and (15), I use per capita income for the year 2005 from the Penn World Tables (version 7.1), and the Gini index from the World Development Indicators for the most proximate year to 2005 available.⁶¹ The resulting parameters are shown in Table A.3 in Appendix D for a total of 104 countries with information available for both Gini and per capita income. As expected, the Gini coefficient is highly correlated with α_j and σ_j , while per capita income is highly correlated with x_j and μ_j .

Once the income distribution for each country is estimated, the second elements needed are the income thresholds (3) that divide overall population into rich and poor consumers from the view of wine consumption. In doing this, I make two simplifying assumptions. First, although the theoretical model suggests that the income thresholds are country-specific, for the empirical results I assume that these thresholds are common to all countries. Second, the model suggests that income perfectly splits the population into consumers of high- and low-quality wine. However, in reality

⁶⁰A more accurate analysis would require individual- or household-level data. Unfortunately, such data is only available for a few countries, making the estimation of income distributions for a large number of countries unfeasible.

⁶¹The Gini index is collected and kindly shared by Crozet et al. (2012).

such separation is not observed: even extremely rich individuals buy a 10-dollar (or cheaper) bottle of wine every once in a while. In the empirical setting, I ignore this possibility and assume instead that income splits population into high- and low-quality wine consumers.

To define the income thresholds, I use the Diary Survey from the 2005 U.S. Consumer Expenditure Survey. This dataset provides information on all daily household purchases – recorded over two weeks – of frequently purchased items, such as food and beverages, and households demographics. The survey has a separate category for wine consumption, and provides information on the cost of the items purchased every week. In addition, the survey collects information on annual income and household size. This allows me first to calculate the average per capita income of each household, and second, to analyze the income distribution of consumers according to the price they pay for wine. In deriving the thresholds I make two arbitrary choices. First, I define as low-quality wine all purchases priced less than 12 dollars, and as high-quality wine purchases priced 20 dollars or more. I intentionally exclude wine priced between 12 and 20 dollars to allow for sharper differences in quality. Second, I define the low-quality income threshold to be equal to the 10th percentile of the income distribution of low-quality wine, and the high-quality income threshold to be equal to the median of the income distribution of consumers buying high-quality wine. The reason for using the median of the income distribution for the case of the high-quality threshold lies in the fact that there is a substantial overlap in the income distribution of both qualities. Since purchases of expensive wines from poor consumers might reflect occasional consumption of high quality as well as other factors, the median income may be more representative of the group consuming high-quality wine on a permanent basis.

As Table 6 shows, the value of the low- and high-quality income thresholds are US\$9,664 and US\$40,164 respectively. Finally, I combine these thresholds with the estimated Pareto and lognormal distributions for each country to derive the fraction of consumers buying high- and low-quality goods.

6.2 Empirical Specification

The main predictions of the model relate country variables to the profitability of each quality segment, and ultimately to the probability of exporting high or low quality to a given destination, through their effect on the productivity thresholds. However, mapping the main implications of the model to the data is difficult, because wineries produce multiple varieties of different qualities and attributes, while in the model firms produce at most one variety of each quality. In this section I explain how I deal with this issue, and present the main specifications used in the empirical results.

The first challenge in the data is to identify high- and low-quality varieties. As I explain in section 3.3, the two main quality indicators I use in this paper are the average price of each brand,

and the self-reported quality appellations labeled on wine bottles. For the first case, I consider high-quality all wine brands with a retail price of over US\$12.⁶² For mapping this value to F.O.B prices per liters, I assume that the winery's price is one-third of the retail wine price.⁶³ This implies an FOB price of of US\$48 for a case of 12 bottles of 750 c.c. For the second case, with quality defined according to quality appellations on the bottle, I define as high-quality wine the categories "Premium" and "Grand Reserve," and as low-quality "Reserve" and "Varietal." Interestingly, Figure 3 suggests that the average price of the Reserve category is just around the 48-dollar threshold set above for defining high-quality wines according to their average prices.

The model has implications for the relative quality composition of firms across destinations. In the empirical part, I map this in terms of two categories of outcome variables. A first set of variables comprises the aggregate exported physical volume (in liters of wine) of high- and low-quality wine. The second set of variables exploits a different margin, comprising instead the number of products of high- and low quality exported to each country by firm. In addition, for each set of variables I consider a third specification with the share of high-quality volume or number of high-quality products as outcome variables. I use this specification for testing the effect of country variables on the relative quality composition of exports.

The main specification studies the effect of average income (Inc), size (Pop), and income inequality (Ineq) on the different measures of quality described above:

$$y_{fjt} = \beta_1 \ln \text{Inc}_j + \beta_2 \ln \text{Pop}_j + \beta_3 \text{Ineq}_j + \beta_4 (\text{Ineq}_j \cdot \ln \text{Inc}_j) + \beta_5 \ln \text{Dist}_j + \beta_6 \ln \text{Rem}_j + \beta_7 \ln \text{Share}_j + \delta X_j + \alpha_{ft} + \varepsilon_{jft} \quad (16)$$

where the subindexes f , j , and t stand for firm, importing country, and year. In all regressions I control for firm-year fixed effects. Thus, the regressions control for the effects of all attributes specific to the firm, such as productivity, technology, and reputation. I proxy for the main explanatory variables – income, size and income inequality – using per capita (in real PPP U.S. dollars), country total population (in millions), and the measures of income inequality presented in the previous section, respectively.⁶⁴ The model predicts that country size and income level increase the

⁶²Wines below this threshold correspond to "Everyday Wines" and "Popular Premium" wines according to the classification performed by Cholette and Castaldi (2005) for the U.S. wine industry in 2005 (see Table 6). However, my main results remain qualitatively unchanged when considering US\$10 and US\$15 as alternative thresholds for defining high- and low-quality wine.

⁶³The evidence reported in Joseph (2012) and Nowack (2007) for the United States and the United Kingdom suggest that the margin is somewhere between one-half and one-fourth for a 10-dollar bottle. I consider the mid-point of this range the benchmark for deriving my results.

⁶⁴Per capita PPP Real GDP and population are taken from the Penn World Tables (version 7.2).

profitability of exporting to a given country, but relatively more for the high-quality segment. Accordingly, I expect $\beta_1, \beta_2 > 0$ when the dependent variable is the physical volume of each quality level, and $\beta_1, \beta_2 < 0$ when the dependent variable is the ratio of high-quality volume to low-quality volume. Regarding the effect of income inequality, proposition 3 predicts a positive relationship between income inequality and relative within-firm quality, which is weaker for richer countries. Thus, I expect $\beta_3 > 0$ and $\beta_4 < 0$ in the specification estimated with the share of high-quality shipments or products as dependent variable.

In equation (16) I control for a number of additional variables. Although some of them have no direct parallel with the theoretical model I included them for robustness. First, I proxy for trade costs by including a variable that accounts for the distance from Santiago – the capital city of Chile –, and a set of geographical categorical variables (represented by the vector X_j). Following Baldwin and Harrigan (2011), instead of using the linear distance to each destination country, I break distance down to bins. The reason for doing this is that since Chile is itself a remote country, including a linear function of distance might not fully reflect the variation in access cost across destinations. I also include several country-specific indicators of access cost used in the gravity literature: categorical variables for common language with Chile (Spanish), whether the country is contiguous to Chile (Argentina, Bolivia and Peru), and for landlocked countries. All geographical variables are taken from the CEPII database. Finally, I use the Comtrade dataset to construct a variable for the market share of Chilean wine exports over total wine imports of each destination country (in millions of liters).

6.3 Results

Table 7 shows the benchmark results for quality defined in terms of quality denominations, and the share of rich and poor consumers derived from the lognormal distribution. Columns 1-3 use physical volume as the dependent variable, while columns 4-6 replicate the analysis using the number of products exported to each destination.

I first discuss the results for physical volume. Columns 1 and 2 of Table 7 show the correlation between country variables and the logarithm of total firm exports of high- and low-quality wines. Results in rows 1 and 2 suggest that in richer and larger countries, both high- and low-quality varieties are exported more intensively. Consistent with the model, the ratio of rich to poor consumers only matters for the level of exports of high-quality varieties (row 3). While I do not derive a formal proposition for non-linear effects of consumer composition according to income level, row 4 in column 1 suggests that the proportion of rich consumers increases shipments of high-quality products only in relatively poor countries.

Column 3 of Table 7 explores the correlation between income, size, and the composition of

consumers in the quality composition of exports. Results in this column support the predictions presented in section 4. First, although small, the effect of average income and size on the share of high-quality exports is negative (rows 1 and 2), implying that in richer and larger countries wineries export a larger volume of low-quality wines. Second, a higher composition of rich consumers increases the relative shipments of high-quality wines (row 3), and consistent with proposition 3, this effect tends to be weaker for richer countries (row 4). The results suggest that the effect of a higher proportion of rich consumers is only significant for middle- and low-income countries: the effect is statistically significant (at the 95% level) only for countries with per capita income below US\$22,000. This income level roughly corresponds to the per capita income of Slovenia.

Columns 4-6 replicate the analysis above, using the number of high- and low-quality products exported to each destination as the dependent variables. In general, the effects are qualitatively similar to the case where physical volume is used as the dependent variable. First, firms ship more high- and low-quality products to richer and larger countries (columns 4 and 5). Second, in countries with relatively more rich consumers, firms ship relatively more high-quality products (column 6). However, in contrast with the case where physical volume was used as the dependent variable (column 3), the share of low-quality products does not seem to be higher in richer or larger countries. This suggests that income and country size affect the quality composition of exports in the extensive margin (exported units), but does not lead firms to introduce relatively more low-quality products.

Alternative Quality Measures and Measures of Relative Distribution

Tables 8 and 9 explore the robustness of the result when quality is defined in terms of the average product price, and when a Pareto distribution is used to derive the fraction of individuals consuming high- and low-quality products. A comparison of these tables to the results in Table 7 reveals a robust relationship between the ratio of individuals consuming high quality and the importance of high quality in total exports and number of products. Importantly, all specifications suggest a nonlinear effect between exports' quality composition and the share of individuals consuming products.⁶⁵ The effect of income and size is also robust across tables, suggesting that firms tend to export more units and products to richer and larger countries. However, in contrast to the benchmark case, results in Tables 8 and 9 do not support the prediction for average income and country size with the share of high-quality products. In most of the cases, the coefficients are

⁶⁵The main difference from Table 7 is that the income threshold for statistically significant effects is lower in these tables. When average price is used to define product quality (Table 8), the threshold falls to about US\$16,000, while the results using Pareto distribution suggest that the effect is only observed in very poor countries. At the 90% confidence level, the threshold in the case of Pareto distribution is estimated to be equal to US\$5,800, which roughly corresponds to the per capita income of Peru and Ecuador in 2005.

insignificant, or even positive.

7 Concluding Remarks

In this paper I study the main implications of including consumer'-side heterogeneity in a model of product quality. I start by documenting that within firms, low-priced varieties account for most of firms' revenues. This fact is inconsistent with quality extensions of models in the spirit of Melitz (2003), and motivates my model, where consumers' income is the main source of heterogeneity.

The model features quality sorting of consumers across their income levels. This implies that the demand for each level of quality depends on the mass of individuals that value the particular quality level and can afford it, which is ultimately determined by the income distribution of each country. The model predicts that in countries with a smaller middle class, firms tend to skew their exports towards products of higher quality. Interestingly, this effect is nonlinear and depends on the average income of the country, being relatively stronger in countries with lower average income. The model also has implications for the effect of country size and average income on firms' quality patterns. According to the model, the profitability of exporting any product increases with country size and average income, but the effect is relatively stronger for low-quality varieties. This suggests that firms' export bundle to richer and larger countries contains relatively more low-quality varieties.

To illustrate the main implications of the model, I use a unique dataset from the Chilean wine industry. The dataset contains detailed information on the attributes of each exported wine variety, and allows me to define quality measures in a more accurate way than the previous literature has. The data gives strong support to the main predictions of the model. I document three main findings. First, firms export higher volume and more products to larger and richer countries. However, in relative terms, firms tend to skew their exports towards low-quality products. This is consistent with the idea that when income distribution is positively skewed, an increase in the size or average income increases relatively more for the fraction of middle-income consumers than for rich consumer. Second, firm-level exports of high-quality products are relatively higher in volume in countries with a smaller middle class. Third, consistent with the main prediction of the model, I find the effect of income distribution to be quantitatively relevant only for middle- and low-income countries. I estimate a threshold income of about US\$22,000-roughly the income level of Slovenia in the year 2005-below which the effect is quantitatively important.

In sum, my results suggest that countries' income distribution matters for understanding the quality composition of firms' exports. Contrary to the previous literature, my results suggest that firms exploit business opportunities in relatively poor countries by concentrating their exports in

the high-quality segments. This result has so far passed under the radar of the literature studying quality patterns of trade, and suggests the existence of welfare gains not studied until now.

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FIGURES

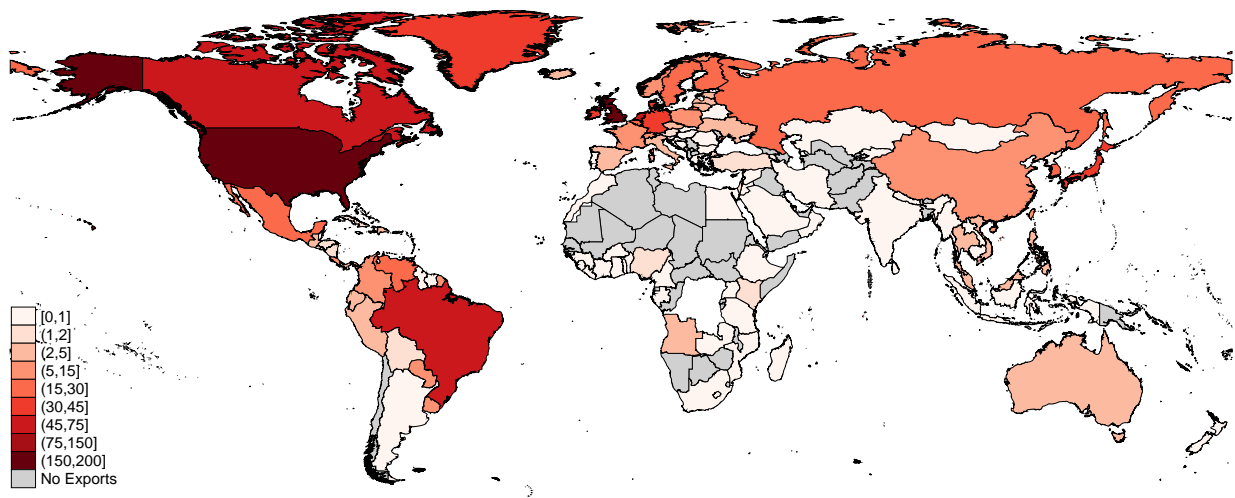


Figure 1: Chilean FOB Exports Value by Importing Country (in US\$ millions, average 2005-2010)

Notes: The Figure shows the average FOB value of bottled Chilean wine exports (HS code 2204.21) to each country over the period 2005-2010. All values are in current U.S. dollars. Countries are shaded to illustrate their import intensity of Chilean wine: darker (lighter) territories import more (less) Chilean wine. The data is from the Chilean Custom Service and provided by Intelvid. See section 3.2 for a more detailed description of the data

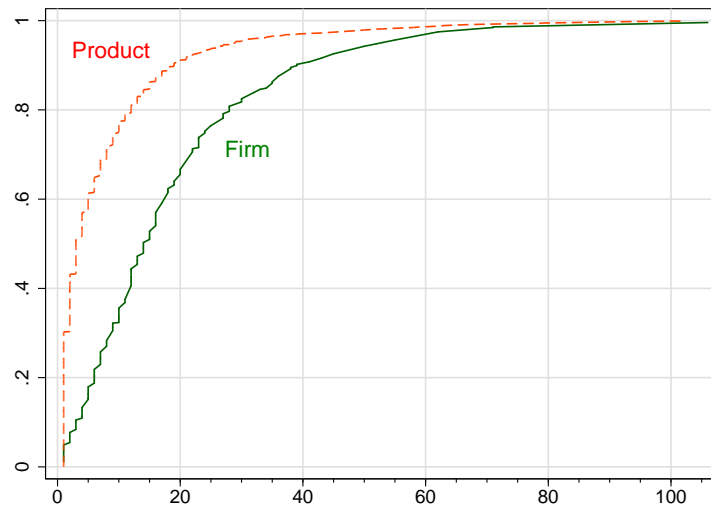


Figure 2: Empirical C.D.F. of Destinations by Firms and Varieties (2007)

Notes: The figure plots the empirical cumulative distribution function across destinations served by firms overall and with each particular product. Products are defined in terms of the brand name printed in the label of each bottle. The underlying data corresponds to the universe of firms producing bottled wine in containers of less than 2,000 c.c. with brand information for the year 2007. Results are qualitatively similar if any other year is used.

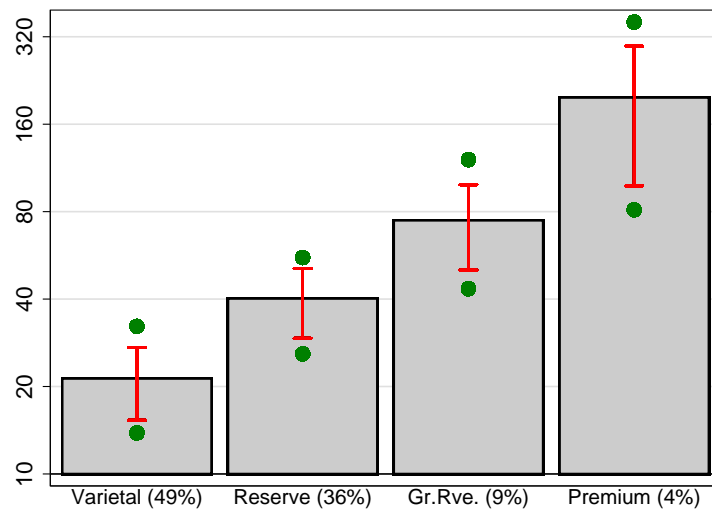


Figure 3: Mean FOB Price by Quality Category (in US\$/ 9 liters box, average 2005-2010)

Notes: The Figure shows the average FOB price (US\$ by 9 liter box) by quality categories for the period 2005-2010. The height of each bar is the unweighted average price for each category, the whiskers show +/-1 standard deviation from the mean, and the green dots show the 5th and 95th percentiles. The numbers under each quality category represents the average share of each quality category in total export revenues. For background on the definition of each quality category, see section 3.3

TABLES

Table 1: Chilean Wine FOB Exports

Year	FOB value (in US\$ million)				Total	Bottled Wine (Value)	
	Bottled	Bulk	Sparkling	Other		% Total	% Comtrade
2005	750.6	108.9	3.8	21.2	884.5	84.9	99.5
2006	830.6	106.5	4.5	21.5	963.1	86.2	99.0
2007	1,088.0	127.1	5.8	40.7	1,261.5	86.2	99.8
2008	1,168.0	144.1	9.9	60.7	1,382.7	84.5	99.5
2009	1,146.0	174.6	9.6	58.1	1,388.3	82.5	99.6
2010	1,281.6	204.0	13.0	56.6	1,555.2	82.4	99.9
Average	1,044.1	144.2	7.8	43.1	1,239.2	84.3	99.6

Notes: The table displays the total free-on-board (FOB) value of Chilean wine exports for the period 2005-2010. Column 2-5 decompose total exports in bottled, bulk, sparkling, and other categories of wine (in box and bag, and made from pulp of fruit). Column 7 computes the ratio of bottled wine value (column 2) to total wine export value (column 6). Column 8 computes the ratio of bottled wine in my sample with official statistics from COMTRADE.

Table 2: Descriptive Statistics, Varieties, and Destinations by Firms and Varieties (2007)

	Mean	St.Dev.	Min	25th Pctile	Median	75th Pctile	Max
# of Varieties	7.2	7.1	1	3	5	23	40
# of Destinations by Firm	18.9	16.8	1	7	14	52	106
# of Destinations by Variety	11.0	14.1	1	3	6	14	102

Notes: Wine prices are expressed in U.S. dollars per 9 liters. For computing the residual prices shown in panel B I run regressions with the logarithm of the FOB price against a constant and the set of fixed effects specified in the corresponding row.

Table 3: Log Price across Firms, Products and Destinations

Fixed Effects	Explanatory Power		St.Dev.
	R ²	Adj. R ²	Residual
None	1%	1%	.846
Destination (<i>j</i>)	5%	4%	.828
Firm (<i>i</i>)	34%	34%	.690
Destination×Firm (<i>ij</i>)	42%	36%	.646
Firm×Variety (<i>ki</i>)	96%	96%	.161

Notes: Results in columns 1-3 show the R², adjusted R² and standard deviation of the residuals from a simple regression of log prices at the variety-level against different sets of fixed effects to illustrate relevance of different margins: $\log P_{kijt} = \{\text{Year FE}\} + \{\text{Other FE}\} + \varepsilon_{kijt}$, where the subscripts (*k, i, j, t*) denotes varieties, firms, destinations and years. Wine prices are expressed in U.S. dollars per 9 liters. For computing the residual prices I run regressions with the logarithm of the FOB price against a constant and the set of fixed effects specified in the corresponding row.

Table 4: Distribution of Varieties by Sales and Price Rank

Price Rank	Sales Rank					Total
	1	2	3	4	5+	
1	0.3	0.1	0.6	0.8	7.3	9.0
2	0.4	1.2	0.8	1.0	5.5	9.0
3	0.6	1.1	1.1	1.4	4.7	9.0
4	0.8	2.1	0.6	1.0	4.6	9.0
5+	6.9	4.4	5.9	4.8	42.1	64.1
Total	9.0	9.0	9.0	9.0	64.1	100.0

Notes: Table displays the joint distribution of Chilean wine brands by within-firm sales and price rank. The top ranked product in each category is assigned a rank equal to 1. See section 3.2 more details on the data description.

Table 5: Distribution of Varieties by Sales and Quality Segment

Price Rank	Sales Rank					Total
	1	2	3	4	5+	
Premium	0.4	0.6	1.3	1.4	7.7	11.4
Grand Reserve	0.7	2.6	2.0	2.7	9.7	17.7
Reserve	4.0	3.7	2.6	2.7	11.4	24.4
Varietal	5.6	3.8	4.8	3.8	28.5	46.6
Total	10.7	10.7	10.7	10.7	57.3	100.0

Notes: Table displays the joint distribution of Chilean wine brands by within-firm sales and quality segment. The top-ranked product in each category is assigned a rank equal to 1. See section 3.2 more details on the data description.

Table 6: Estimated Income Thresholds

Parameter	Value (in Annual US\$)
Low Quality Income Threshold	9,664
High Quality Income Threshold	40,164

Notes: The Table displays the values for the estimated income thresholds (3) (in current U.S. dollars) estimated from the U.S. Consumer Expenditure Survey for the year 2005. The low quality income threshold corresponds to the 10th percentile of the income distribution of households reporting consumption of wine priced 10 dollars or less. The high quality income threshold corresponds to the median of the income distribution of households reporting consumption of wine priced 20 dollars or more.

Table 7: Country Characteristics and Quality Allocation - Benchmark Results

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	<u>log Physical Volume</u>		Share	<u>Number of Products</u>		Share
	High Quality	Low Quality	High	High Quality	Low Quality	High
log Per Capita RDGP	.722*** (.0408)	.787*** (.0347)	-.009* (.00552)	.0826*** (.0261)	.113*** (.0256)	.0003 (.006)
log Population	.444*** (.0147)	.406*** (.0122)	-.003* (.00169)	.0824*** (.00776)	.0878*** (.0112)	.007*** (.002)
Y_j^H / Y_j^L (Consumers' Composition)	15.77*** (4.622)	3.379 (4.431)	1.664*** (.542)	14.03*** (2.318)	15.78*** (3.320)	2.389*** (.595)
× log pc Income	-1.467*** (.442)	-.265 (.424)	-.159*** (.0512)	-1.329*** (.220)	-1.462*** (.316)	-.229*** (.0562)
Firm-Year FE	✓	✓	✓	✓	✓	✓
Geographical Variables	✓	✓	✓	✓	✓	✓
Obs.	6,856	9,253	10,882	10,882	10,882	10,882
R ²	.432	.493	.685	.506	.485	.643

Notes: Regression output corresponds to the estimation of equation (16). The regressions are run at the firm-level, and controls for firm-year fixed effects. The mass of high and low quality consumers (Y_j^H and Y_j^L respectively), are computed from Lognormal income distributions, which fitted for each destination country in the sample (see section 6.1). High-quality brand are defined in terms of their average price across destinations. Quality is defined in terms of the quality denominations embedded in the wine's labels. "Grand Reserve" and "Premium" categories are defined as high-quality brands, while "Varietal" and "Reserve" are defined as low quality wines. Section 3.3 provides further detail. Standard errors (clustered at the firm-year level) in parentheses. Key: ** significant at 1%; * 5%; * 10%.

Table 8: Country Characteristics and Quality Allocation - Alternative Quality Measure

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	<u>log Physical Volume</u>		Share	<u>Number of Products</u>		Share
	High Quality	Low Quality	High	High Quality	Low Quality	High
log Per Capita RDGP	.766*** (.0390)	.772*** (.0362)	.000586 (.00499)	.112*** (.0279)	.0829*** (.0235)	.00609 (.00518)
log Population	.447*** (.0143)	.400*** (.0124)	-.00227 (.00171)	.0996*** (.00844)	.0833*** (.0102)	.00383** (.00158)
Y_j^H / Y_j^L (Consumers' Composition)	4.989 (4.219)	3.251 (4.611)	1.690*** (.573)	15.77*** (2.414)	15.40*** (3.174)	2.332*** (.579)
× log per capita Income	-.427 (.402)	-.255 (.441)	-.166*** (.0545)	-1.496*** (.229)	-1.414*** (.303)	-.228*** (.0550)
Firm-Year FE	✓	✓	✓	✓	✓	✓
Geographical Variables	✓	✓	✓	✓	✓	✓
Obs.	6,856	9,253	10,882	10,882	10,882	10,882
R ²	.432	.493	.685	.506	.485	.643

Notes: Regression output corresponds to the estimation of equation (16). The regressions are run at the firm-level, and controls for firm-year fixed effects. The mass of high and low quality consumers (Y_j^H and Y_j^L respectively), are computed from Lognormal income distributions, which fitted for each destination country in the sample (see section 6.1). High-quality brand are defined in terms of their average price across destinations. The price threshold in this Table is US\$12 per bottle of 750 c.c, and is mapped to F.O.B prices assuming that one-third of the retail price corresponds to the price received by the wineries. Section 6 provides further detail. Standard errors (clustered at the firm-year level) in parentheses. Key: ** significant at 1%; * 5%; * 10%.

Table 9: Country Characteristics and Quality Allocation - Pareto Distributions

Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)
	log Physical Volume		Share	Number of Products		Share
	High Quality	Low Quality	High	High Quality	Low Quality	High
log Per Capita RDGP	.909*** (.0611)	.943*** (.0532)	.00951 (.00585)	.306*** (.0380)	.348*** (.0432)	.0237*** (.00616)
log Population	.442*** (.0142)	.395*** (.0124)	-.00206 (.00172)	.0989*** (.00849)	.0808*** (.0102)	.00401** (.00159)
Y_j^H / Y_j^L (Consumers' Composition)	11.46*** (3.804)	15.86*** (3.605)	.472 (.428)	11.20*** (2.000)	14.91*** (2.328)	1.003** (.464)
× log per capita Income	-1.060*** (.380)	-1.474*** (.363)	-.0558 (.0427)	-1.149*** (.197)	-1.469*** (.234)	-.112** (.0462)
Firm-Year FE	✓	✓	✓	✓	✓	✓
Geographical Variables	✓	✓	✓	✓	✓	✓
Obs.	7,611	8,666	11,119	11,119	11,119	11,119
R ²	.457	.482	.731	.533	.510	.700

Notes: Regression output corresponds to the estimation of equation (16). The regressions are run at the firm-level, and controls for firm-year fixed effects. The mass of high and low quality consumers (Y_j^H and Y_j^L respectively), are computed from Pareto income distributions, which fitted for each destination country in the sample (see section 6.1). High-quality brand are defined in terms of their average price across destinations. Quality is defined in terms of the quality denominations embedded in the wine's labels. "Grand Reserve" and "Premium" categories are defined as high-quality brands, while "Varietal" and "Reserve" are defined as low quality wines. Section ?? provides further detail. Standard errors (clustered at the firm-year level) in parentheses. Key: ** significant at 1%; * 5%; * 10%.