

Quality sorting and trade: Firm-level evidence for French wine*

Matthieu Crozet[†] Keith Head[‡] Thierry Mayer[§]

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Abstract

Investigations of the effect of quality differences on heterogeneous performance in exporting have been limited by lack of direct measures of quality. We examine exports of French wine, matching the exporting firms to producer ratings from two wine guidebooks. We show that high quality producers export to more markets, charge higher prices, and sell more in each market. Our model predicts quality sorting: the more difficult a market is to serve, the better on average will be the firms that serve it. Our findings point to the empirical importance of quality sorting in one industry and could be extended to other industries.

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[†]CEPII and University of Reims.

[‡]Sauder School of Business, University of British Columbia, keith.head@ubc.ca

[§]Université de Paris I, Paris School of Economics, CEPII, and CEPR.

1 Introduction

Why do some firms export more intensively and extensively than others? In the seminal papers of Melitz (2003) and Bernard, Eaton, Jenson, and Kortum (2003) the answer is productivity differences. However, measures of physical output per unit of input are rarely available at the firm level, forcing reliance on proxies like domestic market shares or value-added per worker. These variables can be driven by primitives other than physical productivity, such as product quality. A separate literature on quality and trade relies on noisy proxies (unit values). We study French wine exports, where we are able to match firm-destination-level export flows to firm-level quality ratings from wine guides.

Prior work on quality and trade has examined both the supply side and demand side. Supply side research asks what makes a country export higher quality goods (as inferred from unit values)? Schott (2004) finds that within goods categories, unit values tend to increase with the exporters' per capita income, capital to labor ratio, skill ratio, and the capital intensity of production. Hummels and Klenow (2005) find that, within categories, price and quantity indexes rise with origin-country income per capita. The elasticities are 0.09 (price) and 0.34 (quantity). The authors interpret their price result as showing why big countries do not suffer from a negative terms of trade effect (as they would in a model without quality differentiation). Rather than drive down the value of their single variety, large countries export more varieties and also higher quantities and prices of each variety. Hummels and Klenow also argue in favour of a model with Romer (1994) fixed costs per export market.

Demand-side papers ask what makes country demand a larger share of high quality goods (again inferred from unit values)? Hummels and Skiba (2004) find that average FOB export price rise with freight costs to destination market. They interpret this as a confirmation of the Alchian-Allen (1969) effect ("shipping the good apples out").¹ Hallak (2006) estimates destination-country income effects and find evidence supporting the hypothesis that richer countries have relatively high demand for high quality. Hallak estimates an interaction between unit values (based on the US import data) and income per capita.²

This paper contributes to the quality and trade literature in terms of data and method. "Direct" quality measures compared to "inferred" quality (unit values, market shares). Firm-level quality measures matched to firm-level destination-specific exports. Our model combines the Hallak assumption on preferences for quality with the Baldwin and Harrigan (2007) assumption on the cost of quality. Methodologically, we develop new predictions for the heterogeneous quality model, relating conditional means to market attractiveness measures.

The paper proceeds as follows. We first derive new testable predictions from a model

¹The Alchian-Allen effect relies upon freight costs that are less than proportional to product value. An increase in freight costs therefore lowers the relative price of high quality goods leading to an increase in their relative demand.

²The majority of the coefficients estimated are insignificant or negative and significant. Hallak's "confirmation" of the theory is based upon finding more significant positive than significant negative coefficients.

of firm-level heterogeneity in quality. Then we explain why applying this model to champagne and burgundy producers makes sense. Next we estimate the firm-level equations of that model and back out the implied values of the key structural parameters. Utilizing fixed effects estimated in the firm-level regressions, we estimate the conditional mean relationships implied by the model. Our conclusion suggests a research program based on the success of the quality sorting model as well as the empirical anomalies we find.

2 Theory

The theory examined in this paper is based on work by Baldwin and Harrigan (2007), who introduced a cost-quality tradeoff in the model of Melitz (2003), who introduced productivity-heterogeneity in the model of Krugman (1980), who introduced trade costs to the monopolistic competition model of Dixit and Stiglitz (1977).

2.1 General Set-up

We consider a category of goods (in our case, an 8-digit goods classification) with a sub-utility function that is assumed to have a constant elasticity of substitution (CES), $\sigma > 1$, over the set, \mathcal{B}_j , of all varieties, i available in country j :

$$U_j = \left(\int_{i \in \mathcal{B}_j} [s(i)^\gamma q(i)]^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}. \quad (1)$$

In this expression $q(i)$ denotes quantity of variety i consumed and $s(i)$ denotes its measured quality.³ Following Hallak (2006), the intensity of the consumers' desire for quality is captured in parameter γ . The sub-utility enters full utility with a Cobb-Douglas expenditure parameter denoted μ_j . The foreign country comprises M_j individuals with y_j income per capita.

Our data is based on export declarations which state values in FOB terms. Hence we use x to denote FOB value of export and $p = x/q$ to denote FOB prices. Exports of variety i to market j are given by

$$x_j(i) = \frac{[p_j(i)\tau_j(i)/s(i)^\gamma]^{1-\sigma}}{\int_{\ell \in \mathcal{B}_j} [p_j(\ell)\tau_j(\ell)/s(\ell)^\gamma]^{1-\sigma} d\ell} \mu_j y_j M_j / \tau_j(i), \quad (2)$$

In the above expression prices paid by consumers in j are given by $p_j(i)\tau_j(i)$. Thus $\tau_j(i) - 1$ is the *ad valorem* amount of all trade costs incurred by firm i to sell in market j . As is standard in the literature we assume a single factor of production, constant marginal costs, mill-pricing, the Dixit-Stiglitz markup, and iceberg transport costs. A firm is defined by the trio of $w(i)$, $z(i)$, and $s(i)$. Although we follow the convention of representing factor prices with w , we believe land is the more important factor for wine production. The

³In our application "star" ratings in wine guides provide $s(i)$.

factor price is shown as firm-specific to capture the reality that firms have differing per-unit land costs. The productivity of the factor is denoted with $z(i)$. Hence unit costs are given by $w(i)/z(i)$. Since all our firms are located in close proximity to each other and probably use the same transportation hubs, we approximate their trade costs as being the same for each market, τ_j . Taken together these assumptions imply export revenue from market j is given by

$$x_j(i) = \left(\frac{w(i)/z(i)}{s(i)^\gamma} \right)^{1-\sigma} \mu_j y_j M_j \tau_j^{1-\sigma} P_j^{\sigma-1}, \quad (3)$$

where we have defined the price index in terms of quality-adjusted costs,

$$P_j \equiv \left(\int_{\ell \in \mathcal{B}_j} \left[\frac{w(\ell)/z(\ell)}{s(\ell)^\gamma} \right]^{1-\sigma} d\ell \right)^{1/(1-\sigma)},$$

instead of prices so that the messy term involving the markup, $[(\sigma - 1)/\sigma]^{\sigma-1}$ can cancel out in the numerator and denominator of (2).

The net contribution to firm profits of market j is given by

$$\pi_j(i) = x_j(i)/\sigma - F = ([z(i)/w(i)]s(i)^\gamma)^{\sigma-1} A_j/\sigma - F, \quad (4)$$

where A_j is a factor that aggregates the determinants of the attractiveness of country j defined as

$$A_j \equiv \mu_j y_j M_j (\tau_j/P_j)^{1-\sigma}.$$

Attractiveness depends positively on the size ($\mu_j y_j M_j$) of the market and relative accessibility (which is decreasing in τ_j/P_j).

2.2 The cost-quality tradeoff

We have so far allowed for heterogeneity in productivity (the standard approach following Melitz (2003)), factor prices (an important consideration for wine producers), and quality. Three sources of heterogeneity is two too many for a tractable model. One option is to hold w/z constant and have a model of pure (costless) quality variation. The problem with this is that in the Dixit-Stiglitz framework, mark-ups do not vary across firms and so quality has no independent effect on price. To account for the stylized fact that higher quality is associated with higher prices in this framework, we follow Baldwin and Harrigan in assuming a deterministic tradeoff between cost and quality. We discuss the reasons to expect such a relationship for wine in section 3.

Because we observe quality directly, and therefore want to focus on that variable, we modify the parameterization of the cost-quality tradeoff slightly differently from Baldwin and Harrigan but this only matters for the exposition. Rather than assume firms draw a unit labour requirement ($1/z$), we assume firms draw a level of quality (s).

We assume that when firms take a high quality draw that a cost must be paid in terms of higher factor prices and/or lower productivity. Thus we assume,

$$\frac{w(i)}{z(i)} = \omega s(i)^\lambda, \quad (5)$$

with $\lambda \geq 0$. Our parameter is related to the one used in Baldwin and Harrigan as follows: $\lambda = 1/(1 + \theta)$. For $\lambda = 0$, quality is costless and firms have unit factor costs given by ω no matter what quality they draw. Another useful special case is $\lambda = -1$. That value, combined with $\gamma = 0$ makes it possible to reinterpret $s(i)$ as a productivity draw since it implies $w(i)/z(i) = \omega/s(i)$. This allows us to compare the results of the quality-sorting model ($\gamma > 0, \lambda \geq 0$) with the original Melitzian productivity sorting model ($\gamma = 0, \lambda = -1$).

2.3 Entry threshold quality

Substituting (5) into (4), we obtain

$$\pi_j(i) = \omega^{1-\sigma} s(i)^{(\gamma-\lambda)(\sigma-1)} A_j / \sigma - F, \quad (6)$$

For $\gamma > \lambda$, quality is valued at more than it costs to produce it, so a high s draw increases profits. Solving for the zero-profit cutoff quality for market j as

$$\hat{s}_j = \left(\frac{A_j}{\sigma F \omega^{\sigma-1}} \right)^{\frac{-1}{(\sigma-1)(\gamma-\lambda)}}. \quad (7)$$

As long as $\gamma > \lambda$ it will be the case \hat{s}_j is the *minimum* level of quality required to enter market j . This cut-off will be increasing in fixed costs and decreasing in the attractiveness of the market. For $\gamma < \lambda$, quality is not worth the cost and a lucky firm draws a low s . Thus, \hat{s} becomes the *maximum* quality level.

If γ varies across countries then it is possible that, for some countries, \hat{s} would be a minimum and, for others, it is a maximum. Hallak (2006) assumes a positive semi-log relationship between per-capita income and the intensity of preference for quality:

$$\gamma_j = \gamma_0 + \gamma_1 \ln(y_j/y_0), \quad (8)$$

with $\gamma_1 > 0$. Hallak's original specification did not include y_0 . In his model γ_0 is the intensity of preference for a hypothetical country with $y_j = 1$. In our specification $\gamma_j = \gamma_0$ for $y_j = y_0$. By setting $y_0 =$ to the world average we obtain a convenient interpretation for estimates of γ_0 .

For quality to be desirable for exporting to market j —and therefore for \hat{s}_j to represent a minimum—it must be that $\ln y_j > \ln y_0 + (\lambda - \gamma_0)/\gamma_1$. We assume for the purposes of calculating conditional expectations that this condition is met for all j but we will reconsider when we look at the data.

When this condition is met, the interpretation of (7) is straightforward. The level of quality needed to enter market j is a negative function of how “easy” this market is for French exporters, which is captured by A_j . On the contrary, higher costs, either fixed (F) or variable (ω) increase the quality cut-off, which means that lower quality firms will not be able to sell abroad. This is for the quality draw model. Note that the logic is the same in the efficiency draw case, where $\gamma = 0$ and $\lambda = -1$. In the ED model, the productivity cut-off level decreases with ease of market A_j and increases with costs.

To obtain closed form solutions, we follow much of the recent literature in assuming a Pareto distribution for heterogeneity. Thus, assume that the CDF, $G(s)$, and PDF, $g(s)$, take the forms

$$G(s) = 1 - (s/\underline{s})^{-\kappa}, \quad \text{and} \quad g(s) = \kappa \underline{s}^\kappa s^{-\kappa-1}. \quad (9)$$

The total pool of firms that might export to market j is given by N_x , which we consider as an exogenous variable here. The share of firms exporting to a market j is

$$N_j/N_x = \Pr(s > \hat{s}) = 1 - G(\hat{s}) = (\hat{s}/\underline{s})^{-\kappa}. \quad (10)$$

Plugging in equation (7) for \hat{s}_j we can express the number of exporters to a market as a function of the attributes of the market.

$$N_j = N_x \left(\frac{A_j}{\sigma F \omega^{\sigma-1}} \right)^{\frac{\kappa}{(\sigma-1)(\gamma-\lambda)}} \underline{s}^\kappa \quad (11)$$

The variable A_j collects a potentially large set of variables, some of which (e.g. trade costs) are difficult to measure. An alternative approach is invert equation (10) to express the critical entry threshold as a function of the number of entrants:

$$\hat{s}_j = G^{-1}(1 - N_j/N_x) = (N_j/N_x)^{-1/\kappa} \underline{s} \quad (12)$$

In this formulation N_j/N_x can be thought of a single index of the ease of entering market j . This has the advantage of compactness, and will be useful in particular as a graphical device. We will also however present results in terms of the primitives of the model, and in particular A_j and its underlying components, for testing models' predictions in regression analysis, using (7) rather than (12). We now proceed to detailing those predictions in terms of measurable aggregate statistics: the average quality, average price and average quantity on each destination market j .

2.4 Conditional mean quality

The average quality of exporters to a given market is $E[s \mid s > \hat{s}]$. The general form for the expected value of a variable truncated from below is

$$E[s \mid s > \hat{s}] = \frac{1}{1 - G(\hat{s})} \int_{\hat{s}}^{\infty} s g(s) ds.$$

The expected value of a truncated Pareto is

$$E[s \mid s > \hat{s}] = \hat{s} \frac{\kappa}{\kappa - 1}. \quad (13)$$

Then substituting (12) into equation (13), we remove the unobserved threshold and obtain the observed conditional mean quality of exporters to a market as a function of the observed number of exporters to that market

$$E[s \mid s > \hat{s}] = \left(\frac{N_j}{N_x} \right)^{-1/\kappa} \underline{s} \frac{\kappa}{\kappa - 1} \quad (14)$$

This negative relationship between average quality and popularity presumes truncation from below, which occurs for *sufficiently high income countries*, the ones that place importance on quality.

To obtain the prediction in terms of the primitives, substitute (7) into equation (13), and obtain

$$E[s \mid s > \hat{s}] = \left(\frac{A_j}{\sigma F \omega^{\sigma-1}} \right)^{\frac{-1}{(\sigma-1)(\gamma-\lambda)}} \frac{\kappa}{\kappa-1} \quad (15)$$

The testable predictions are straightforward. Anything that makes a market more attractive (higher A_j) will reduce the average level of quality (in the QD model) or the average level of productivity (in the ED model) measured for exporters to market j . In a reduced form equation A_j can be approximated as a positive function of market size and a negative function of distance (or any other measurable proxy for trade costs to j). Average performance (quality or efficiency) of French exporters in j should therefore decrease with GDP in j and increase with distance to j . Note that if fixed costs were also a function of distance, it should be a positive one, and the overall prediction is unchanged: more distant markets should exhibit higher average performance (quality or efficiency). Assessing which type of sorting is actually taking place requires measures of individual quality and efficiency, which is not always available. There are, however, some discriminating predictions between the two models to which we now turn.

2.5 Conditional mean price

With Dixit-Stiglitz pricing behavior and the cost-quality relationship embodied in equation (5), individual firms charge FOB prices of

$$p_j(i) = \frac{\sigma}{\sigma-1} \omega s(i)^\lambda. \quad (16)$$

These prices do not vary across destination markets. A more general model might incorporate such variation either via cross-country differences in σ , and hence the mark-up. The mean price conditional on exporting does vary across markets:

$$E[p \mid s > \hat{s}] = \frac{1}{1 - G(\hat{s})} \int_{\hat{s}}^{\infty} p(s) g(s) ds = \frac{\omega \sigma}{(\sigma-1)(1 - G(\hat{s}))} \int_{\hat{s}}^{\infty} s^\lambda g(s) ds. \quad (17)$$

Evaluating this expression for a Pareto distribution, we obtain⁴

$$E[p \mid s > \hat{s}] = \frac{\hat{s}^\lambda \omega \sigma \kappa}{(\sigma-1)(\kappa-\lambda)}. \quad (18)$$

Using equation (12) to substitute out the unobservable \hat{s} we obtain

$$E[p \mid s > \hat{s}] = \left(\frac{N_j}{N_x} \right)^{-\lambda/\kappa} \frac{\underline{s}^\lambda \omega \sigma \kappa}{(\sigma-1)(\kappa-\lambda)}. \quad (19)$$

⁴For the integral to be finite we need $\kappa > \lambda$.

As with mean quality, the mean price conditional on exporting is decreasing in N_j/N_x for the QD model. However, the prediction is opposite for the ED model, which you obtain by setting $\gamma = 0$ and $\lambda = -1$. When quality sorting takes place, only high quality varieties get exported to difficult countries, and those are high price varieties, because high quality is associated with high costs in our setting. When efficiency sorting is the driver of firms' selection into export markets, only the most productive firms with low marginal cost make it to difficult markets, and -with a constant markup- those have a low price.

In terms of the primitives, the prediction on average price is the following:

$$E[p \mid s > \hat{s}] = \left(\frac{A_j}{\sigma F} \right)^{\frac{-\lambda}{(\sigma-1)(\gamma-\lambda)}} \frac{\omega^{\frac{\gamma}{\gamma-\lambda}} \sigma \kappa}{(\sigma-1)(\kappa-\lambda)}. \quad (20)$$

Recall that attractiveness, $A_j \equiv \mu_j y_j M_j \tau_j^{1-\sigma} P_j^{\sigma-1}$. In the QD model, where $\gamma > \lambda > 0$, the average price should therefore be a negative function of population (M_j), income per capita y_j and taste for wine μ_j . It should however be increasing in distance d_j , which enters τ_j (and possibly F_j) positively. A reduced form equation of the QD model can be estimated in the following form:

$$\ln E[p \mid s > \hat{s}] = \alpha_0 + \alpha_1 \ln M_j + \alpha_2 \ln y_j + \alpha_3 \ln d_j + \epsilon_j, \quad (21)$$

where $\alpha_1, \alpha_2 < 0$ and $\alpha_3 > 0$. This is a reduced form equation since i) not all components of trade costs are controlled for, ii) the fixed cost is left constant⁵, iii) the unobservable preference parameter μ_j and price index P_j are left in the disturbance term. The ED model calls for opposite coefficients on all those variables, enabling for a discriminating test between those two views of exporters' sorting.

2.6 Conditional mean quantity exported

Exports of variety i , expressed as a function of quality are given by

$$x_j(i) = \omega^{1-\sigma} A_j s(i)^{(\gamma-\lambda)(\sigma-1)} \quad (22)$$

The quantity exported by a firm with quality s can be obtained by dividing (22) by the equation for FOB prices, (16):

$$q_j(i) = \frac{\sigma-1}{\sigma} \omega^{-\sigma} A_j s(i)^{(\sigma-1)\gamma-\lambda\sigma} \quad (23)$$

The conditional mean quantity is therefore given by

$$E[q \mid s > \hat{s}] = \frac{\sigma-1}{\sigma} \frac{\omega^{-\sigma} A_j}{1-G(\hat{s})} \int_{\hat{s}}^{\infty} s^{(\sigma-1)\gamma-\lambda\sigma} g(s) ds. \quad (24)$$

⁵As mentioned above however, if fixed costs of serving j are increasing in distance d_j , the prediction on the signs of coefficients is left unaffected.

Evaluating this expression for a Pareto distribution and assuming $\kappa > \gamma(\sigma - 1) + \lambda\sigma$ for finiteness, we obtain

$$\mathbb{E}[q \mid s > \hat{s}] = \frac{\hat{s}^{(\sigma-1)\gamma-\lambda\sigma} A_j \omega^{-\sigma} \kappa \sigma - 1}{\kappa - (\sigma - 1)\gamma + \lambda\sigma \sigma}. \quad (25)$$

This expression is more complex than the average price. Indeed, *both* A_j and \hat{s} enter average exports, while only \hat{s} enters average price. The reason has to do with the intensive and extensive margins of trade increases in this model. In a Dixit-Stiglitz setup, prices are a constant markup over marginal costs, and in particular do not depend on market size or anything that enters A_j . Therefore, a rise in market attractiveness A_j impact prices only through the extensive margin, the entry of firms into export market j , the \hat{s} term in (18). Quantities sold by each firm that exports to j do however depend on A_j . Consequently, (25) depends on the extensive margin \hat{s} , but also on the intensive one through the independent impact of A_j .

Using the zero-profit condition, $A_j = F\sigma\omega^{\sigma-1}\hat{s}^{(\lambda-\gamma)(\sigma-1)}$, we can reduce this to⁶

$$\mathbb{E}[q \mid s > \hat{s}] = \frac{\hat{s}^{-\lambda} F \kappa (\sigma - 1) \omega^{-1}}{\kappa - (\sigma - 1)(\gamma - \lambda) + \lambda}. \quad (26)$$

Using (12) we can remove \hat{s} and are left with a expression in terms of number of entrants.

$$\mathbb{E}[q \mid s > \hat{s}] = \left(\frac{N_j}{N_x} \right)^{\lambda/\kappa} \frac{\underline{s}^{-\lambda} F \kappa (\sigma - 1)}{\omega(\kappa - (\sigma - 1)(\gamma - \lambda) + \lambda)}. \quad (27)$$

Average quantity to j is a positive function of popularity, N_j/N_x , in the case of the QD model, and again the sign of the relationship is inversed when the ED model is considered and $\lambda = -1$.

Turning to primitives, in order to obtain a reduced-form testable equation, we substitute (7) in (25) to obtain

$$\mathbb{E}[q \mid s > \hat{s}] = \left(\frac{A_j}{\sigma} \right)^{\frac{\lambda}{(\sigma-1)(\gamma-\lambda)}} F^{\frac{(\sigma-1)\gamma-\sigma\lambda}{(\sigma-1)(\gamma-\lambda)}} \frac{\omega^{\frac{-\gamma}{(\gamma-\lambda)}} \kappa (\sigma - 1)}{\kappa - (\sigma - 1)(\gamma - \lambda) + \lambda}. \quad (28)$$

The power on A_j is positive as long as quality is “worthwhile,” i.e. $\gamma > \lambda$. Under the parameterization corresponding to the ED model ($\gamma = 0$, $\lambda = -1$), the power on A_j is $-\sigma/(\sigma - 1) < 0$. The power on F is greater than one in the QD model.

Again, with $A_j \equiv \mu_j y_j M_j \tau_j^{1-\sigma} P_j^{\sigma-1}$, a reduced form equation of the QD model can be estimated in the following equation:

$$\ln \mathbb{E}[q \mid s > \hat{s}] = \beta_0 + \beta_1 \ln M_j + \beta_2 \ln y_j + \beta_3 \ln d_j + \epsilon_j. \quad (29)$$

⁶Using the same steps for the export value to each country j leads to the striking result that the conditional mean of values exported to a market j does *not* depend on anything else than fixed costs, and in particular does not depend on A_j . This is true in both our quality sorting model and in the efficiency sorting model, as was recently emphasized by Lawless and Whelan (2007).

When F does not vary across countries, the prediction is very simple and opposite to the one on prices: $\beta_1, \beta_2 > 0$ and $\beta_3 < 0$. This is a reduced form equation for the same reasons as the price equation. Again, the ED model calls for opposite coefficients on all those variables, enabling for a discriminating test between those two views of exporters' sorting. In the QD model, easy markets see lower quality firms on average export high quantities of low price goods. In the ED case, those same high A_j countries face exports by less efficient firms on average that charge high prices and sell less.

There appears to some ambiguity regarding the F term. Suppose that F_j is a positive function of d_j . In the average price equation, the sign prediction on α_3 is unchanged since τ_j and F_j are raised to the same power in (20). This is not the case in the mean quantity equation (28) since $(\sigma - 1)\gamma - \sigma\lambda > 0$ as long as $\gamma > \lambda > 0$ and $\sigma > 1$. In that case, d_j has a positive influence on average quantity through F_j and a negative one through τ_j in A_j . Note that in the ED parameterization, the distance should unambiguously *raise* average quantity.

Table 1 summarizes this large set of predictions.

Table 1: Predicted elasticities in two sorting models

Sorting model:	Explanatory variable:	Dependent variable:			
		N_j	\tilde{s}_j	\tilde{p}_j	\tilde{q}_j
$s = \mathbf{quality}$ $(\gamma > \lambda \geq 0)$	“popularity” (N_j)		$\frac{-1}{\kappa}$	$\frac{-\lambda}{\kappa}$	$\frac{\lambda}{\kappa}$
	“attractiveness” (A_j)	$\frac{\kappa}{(\sigma-1)(\gamma-\lambda)}$	$\frac{-1}{(\sigma-1)(\gamma-\lambda)}$	$\frac{-\lambda}{(\sigma-1)(\gamma-\lambda)}$	$\frac{\lambda}{(\sigma-1)(\gamma-\lambda)}$
$s = \mathbf{productivity}$ $(\gamma = 0, \lambda = -1)$	“popularity” (N_j)		$\frac{-1}{\kappa}$	$\frac{1}{\kappa}$	$\frac{-1}{\kappa}$
	“attractiveness” (A_j)	$\frac{\kappa}{\sigma-1}$	$\frac{-1}{(\sigma-1)}$	$\frac{1}{\sigma-1}$	$\frac{-1}{\sigma-1}$

2.7 Firm-level predictions

We can estimate the model using firm-level data for three different dependent variables: the probability of exporting, the FOB price, and exported quantity. Taking logs of equations (6), (16), and (23) we can obtain estimating equations.

The probability of exporting is given by

$$\Pr(x_j(i) > 0) = \Pr(\pi_j(i) > 0) = \Pr(\ln x_j(i) - \ln \sigma > \ln F).$$

Without some additional source of heterogeneity, this probability would be one for $s(i) > \hat{s}_j$ and zero otherwise. One way of introducing firm-level uncertainty is to assume that the fixed costs of exporting to country j for firm i , $F_j(i)$ vary depending on a common component f , and a firm-country unobservable term $\epsilon_j(i)$. From (6), firm i will export to j with probability:

$$\Pr(x_j(i) > 0) = \Pr[(1 - \sigma) \ln(\omega/f\sigma) + \ln A_j + (\gamma - \lambda)(\sigma - 1) \ln s(i) > \epsilon_j(i)]. \quad (30)$$

The parameters of this probability can be estimated by probit or logit depending on the assumption made on the distribution of the error term $\epsilon_j(i)$. We use logit because it can absorb the country-year fixed effects for the A_j .⁷

From (16), the price charged by firm i takes the following estimable form:

$$\ln p_j(i) = \ln[\sigma/(\sigma - 1)] + \ln \omega + \lambda \ln s(i), \quad (31)$$

From (23), the firm-level exported quantity is

$$\ln q_j(i) = \ln[(\sigma - 1)/\sigma] - \sigma \ln \omega + \ln A_j + [(\gamma - \lambda)(\sigma - 1) - \lambda] \ln s(i). \quad (32)$$

For export probabilities and quantities, $\ln A_j$ appears on the RHS. Rather than attempt to estimate this term as a parametric function of country j primitives, we absorb it with country-year-specific fixed effects. Firm-level prices do not vary across destinations in the model but it is natural to relax the strong assumption of non-varying σ . In that case the structural interpretation of the country level fixed effect in the price equation is $\ln[\sigma_j/(\sigma_j - 1)]$.

We have also estimated a semi-parametric form of these regressions in which we replace $\ln s(i)$ with a set of indicator variables corresponding to the number of stars accorded to the producer. Our initial assessment was that the gain from more flexibility was not high enough to offset the cost in terms of the inability to extract estimates of γ and λ and the greater number of coefficients to report and discuss.

3 Why Wine?

Champagne (nc8 22041011) and red burgundy (nc8 22042143) have built reputations for non-replicable attributes. Thus, they exhibit Armington-style differentiation by *place* of origin. With Champagne this is an organized legal and promotional effort. To qualify as champagne in the EU (and Canada), a wine must be produced within the Champagne geographic *appellation*.

“The important thing to remember is that while some processes of Champagne production may be duplicated, the terroir is unique, original, and impossible to replicate.” (www.champagne.us)

⁷The Stata command is “xtlogit, fe”

Some wine critics agree with the proposition that sparkling wine from Champagne is distinct:

“The Champagne region has certain natural advantages that no amount of money, ambition, or talent can surmount: The combination of chalky soil and fickle northern European weather yields sparkling wines that simply can’t be replicated anywhere else, or at least anywhere that’s been tried.” (Steinberger, 2005)

Burgundy producers do not invest in such overt promotion of their regional identity. However, wine critics tend to judge pinot noir wines relative to the Burgundian style. Furthermore, the most expensive wines in the world are red burgundies.

The relevance for this study is that Melitz (2003) model, upon which we base our analysis, assumes that firms face only the option of exporting or not to a given market. They cannot relocate production as in the Helpman, Melitz, Yeaple (2004) framework. With footloose production, the implications for quality sorting could be quite different. Thus, the geographic definition of champagne and burgundy makes these goods particularly appropriate for studying the effect of heterogeneity on the composition of exporters by destination.

While the model rests upon a product that is not reproducible in the export market, it also insists on firm-level differentiation within each country. Champagne fits this assumption well. Geographic distinctions *within* champagne region (a single *appellation*) are not emphasized.

“[E]ssence of champagne is that it is a blended wine, known in all but a handful of cases by the name of the maker, not the vineyard.” (Johnson and Robinson, 2005)

Quality determined by cellar-master’s talent at blending, “dosing,” etc. Sales policy emphasizes the brand.

In Burgundy, on the other hand, there are many small *appellations*, each of which is supposed to have distinct properties. Within the *appellations*, vineyards are further stratified into village wines, *premier cru* and *grand cru*. Many different producers typically make wine from grapes from the same *grand cru* vineyard. Conversely most producers have obtain grapes from multiple vineyards. Burgundians attribute most quality variation to place-specific *terroir*: the soil, topography, and microclimate. Comparing across wines from the same vineyard, they also emphasize vintage: year-specific weather. Since our data does not report the vineyard or the vintage of the wine exported, it would appear ill-suited to capture quality variation in burgundy wine. However, Robert Parker, the most influential wine critic in the world, asserts that there are large within-vineyard quality differences due to firm-specific variation in viticulture and vinification practices.

“Knowing the finest producers in Burgundy is unquestionably the most important factor in your success in finding the best wines.”

There are several mechanisms supporting a cost-quality tradeoff in wine. First there is the cost of acquiring land with the desirable *terroir* properties. In Burgundy “village vineyards” cost €150–500K/ha (Robinson, 20??). Assuming an interest rate of 5% and a typical yield of 5000 bottles per hectare, this corresponds to a unit land cost of €1.5–5 per bottle. On the other hand, land that has been designated as a *grand cru* vineyard costs over €2M/ha, or more than €20 per bottle. In the Champagne region the major, where the quality of land has been built into the price of grapes through the system called *échelle des crus*. Thus if we think of $w(s)$ as the factor costs embodied in wine of quality s , we have good reasons to expect $w' > 0$.

Wine is also believed to exhibit a trade-off between yield and quality. Low-yield viticulture, which involves pruning back vines from 40 hectolitres per hectare (the average in Burgundy) to 20 hl/ha (the yield at the Romanée Conti vineyard) doubles unit land costs. However, Parker and most other wine experts argue that this raises flavour concentration. Indeed the importance of yield is recognized in much of the AOC regulation in France which sets allowable yield levels by *appellation*.

The process of winemaking itself also exhibits cost-quality tradeoffs. One familiar example is the use of new oak barrel. The advantage of new oak is that imparts more flavour into the wine. However, our calculations indicate that it adds something in the neighborhood of €2 to the cost of each bottle.

4 Data

4.1 Trade data

We use the micro-data collected each year based on export declarations submitted to French Customs. It is an almost comprehensive database which reports annual individual shipments of each French exporting firms. The “almost” is due to EU legislation following the implementation of the single market, which set different thresholds for compulsory declarations inside and outside the customs union. Inside the EU, shipments are reported if their annual trade value exceeds 250,000 euro. Exports outside the EU are recorded unless their value is smaller than 1000 euros or one ton. For each firm, Customs records values and quantities exported to 216 importing countries, and 11,578 8-digit product classifications (combined *nomenclature*, which is abbreviated as “nc8”). We have observations for the six years from 1998 to 2003.

The nc8 is the harmonized system 6-digit (hs6) code with a 2-digit suffix that is particular to the European Union. Wine has hs4 of 2204. Sparkling wine is 220410 and still red wine less in less than two liter containers is 220421. For our purposes is fortunate that the last two digits of nc8 distinguish important wine-growing regions in the EU. Thus champagne, the sparkling wines of the official Champagne region are recorded as nc8 # 22041011. Furthermore, red wines from the Burgundy wine region is classified as nc8 # 22042143.

Champagne and red burgundy account for 0.45% and 0.048% respectively of French manufacturing trade. This might not seem much per se, but it is rather large compared

to other industries. The mean industry-level contribution to total trade is less than 0.01% and the largest exporting industry (aeroplanes and other aircraft exceeding 15 tons) accounts for 3.24% only. Our two industries are clearly among the largest 5% of contributors to French trade. They also are strong outliers in other dimensions. When ranking nc8 products according to number of exporting firms, champagne and red burgundy rank 21st and 65th respectively out of 11,578 products. Their importance is even more striking in terms of the number of destination countries. As figure 1 shows, those two industries export to a much larger number of countries than the typical French industry.

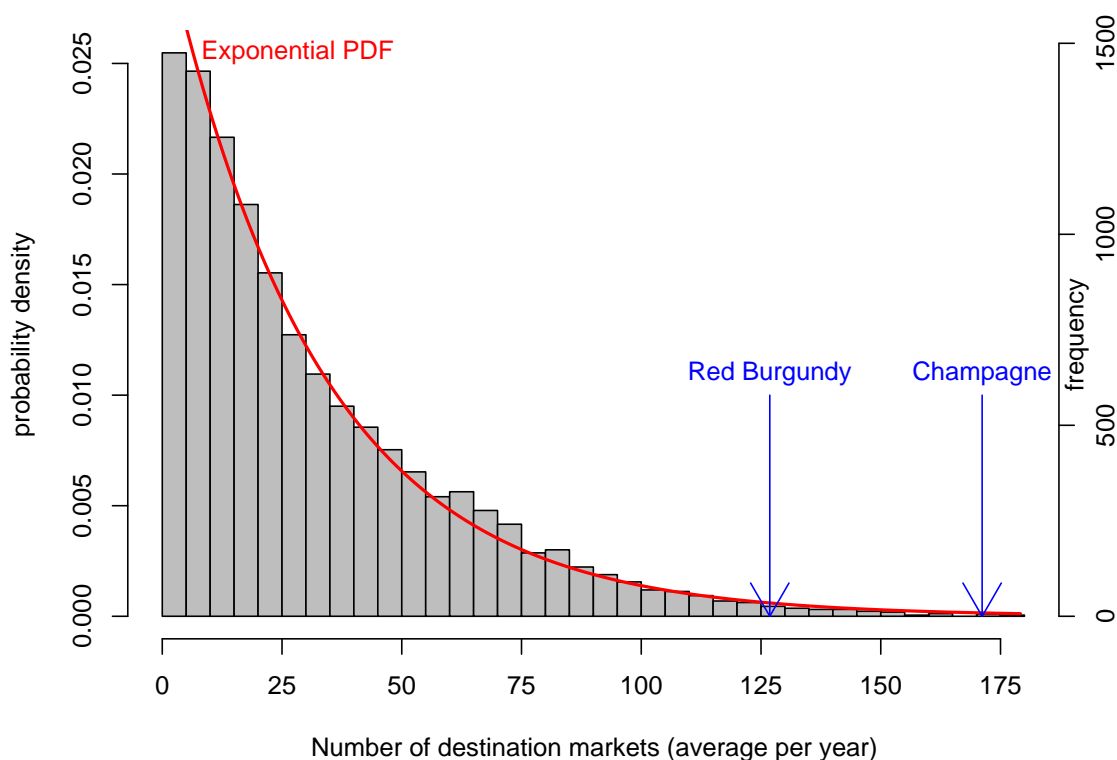


Figure 1: Champagne and Wine are outliers in the distribution of destinations per product

The export declaration data provided us with firm identification numbers, or SIREN, for all 12,314 firms who exported any form of wine ($hs4 = 2204$) between 1998 and 2003. Of those, the French National institute (INSEE) provided us with the names, addresses, principal industry code, and other attributes of 10,341 firms in existence as of June 2007. We used the firm-level information to match our exporters with wine producers that were rated in two guidebooks.

4.2 Quality ratings

Wine producer quality ratings come from two different sources: i) a French one: Burtschy, Bernard and Antoine Gerbelle, 2006, *Classement des meilleurs vins de France*, Revue Des

Vins De France (Paris), which we will refer to as RVF, ii) an internationally recognized one: Parker, Robert, *Wine Buyer's Guide*, 5th Edition, 1999, which we refer to as WBG. For each of the listed producers, the name and location were matched with the exporter's dataset by hand.

In RVF, listed producers receive between 0 and 3 stars. We have 64 champagne producers listed, and are able to match those with 51 exporters. For burgundy, 268 are listed, of which 206 can be found in the customs dataset. In WBG, producers (70 for champagne, and 159 for burgundy) are categorized as "average," "good," "excellent," or "outstanding." Of those we manage to find 47 champagne exporters and 139 burgundy exporters.

Table 2: Champagne quality ratings

Parker's WBG	RVF's <i>Classement</i>					Total
	n/a	Incl.	*	**	***	
n/a	1724	16	6	0	0	1746
Average	3	1	0	0	0	4
Good	7	3	1	2	0	13
Excellent	7	6	4	3	0	20
Outstanding	1	0	3	4	2	10
Total	1742	26	14	9	2	1793

Note: Kendall's τ measure of concordance $-1 \leq \tau \leq 1$ (p -value for test for independence), all exporters: 0.58 (0.000) / included in both books: 0.43 (0.009).

Table 3: Burgundy quality ratings

Parker's WBG	RVF's <i>Classement</i>					Total
	n/a	Incl.	*	**	***	
n/a	1389	69	44	20	4	1526
Average	19	7	6	4	1	37
Good	28	4	4	12	1	49
Excellent	11	1	11	14	1	38
Outstanding	4	1	4	3	3	15
Total	1451	82	69	53	10	1665

Note: Kendall's τ measure of concordance $-1 \leq \tau \leq 1$ (p -value for test for independence), all exporters: 0.39 (0.000) / Included in both books: 0.22 (0.023).

Customs data lists exports by a firm for each nc8 product. However, in other firm-level sources of data, firms are classified according to a "primary" activity. It appears actually

that a large proportion of wine exporters are not referenced as producers. Some of those “non-producing” exporters are dealers who mainly label and distribute wine made by other firms. Other firms are mainly dealers, but are also vertically integrated backwards into vinification and even viticulture.

Table 4: Who exports wine?

activity	code	description	Export shr.	
			Cham.	Burg.
growers	011G	viticulture (grapes)	2%	24%
makers	159F/G	vinification (wineries)	74%	4%
dealers	513J	bev. wholesalers	7%	62%
others	—	admin., interm., ...	16%	10%

Table 5: Champagne: # of exporters/destinations

Primary Activity	Quality-Rated? Local Dept?	No		Yes
		No	Yes	Yes
grower		40	392	22
		76	3972	1015
maker		10	84	33
		50	2914	5846
dealer		346	94	10
		1624	2229	769
other		678	101	4
		2923	1166	824

We have to select a group of low quality producers. We cannot rely only on the group of exporters that are excluded from the ratings. It seems desirable to exclude from our analysis all firms that ship wine abroad but for which we are unable to judge quality of the wine exported. This happens for dealers that are not rated, who presumably export all sorts of wine. Those enter a category we refer to as “mixed” in figures 2 and 3. For producers, we consider as low quality firms, the ones that are unrated by either guide and located within the “right” areas, that is the relevant grape-growing départements. Unrated producers from other areas also enter the mixed category.

There are several issues that can be raised with guidebook ratings as quality measures:

Figure 2: Markets/firm

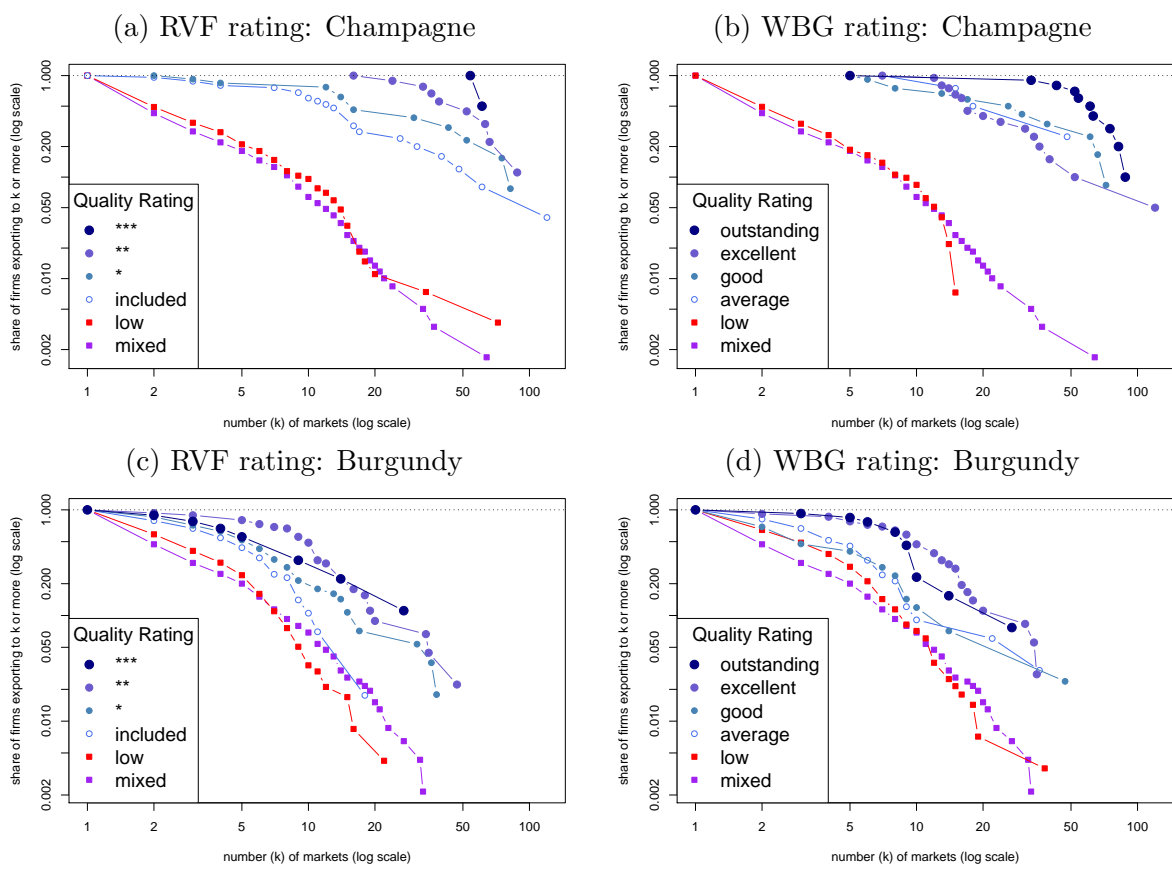
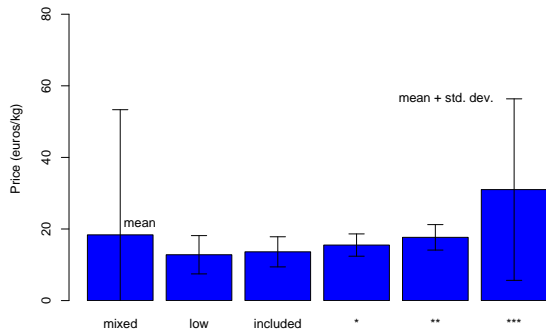
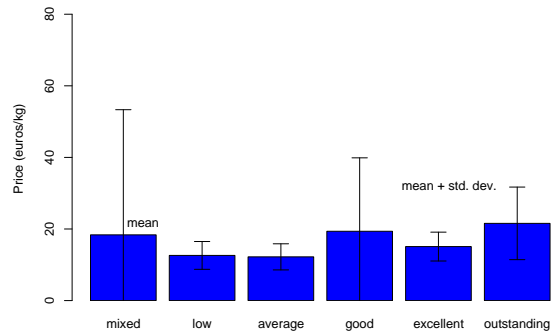


Figure 3: Price (wt. avg.)

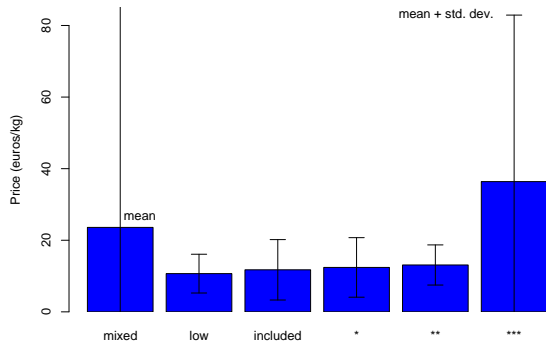
(a) RVF rating: Champagne



(b) WBG rating: Champagne



(c) RVF rating: Burgundy



(d) WBG rating: Burgundy

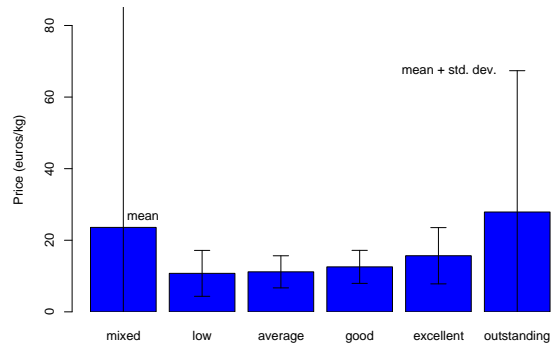


Table 6: Burgundy: # exporters/destinations

Primary Activity	Quality-Rated? Local Dept?	No		Yes	
		No	Yes	No	Yes
grower		91	303	1	170
		175	3276	2	4554
maker		21	20		5
		136	482		182
dealer		298	157	6	62
		1922	3739	98	3159
other		356	143	2	30
		1346	1112	54	643

1. *The ratings are hard to interpret:* units of measurement (stars) do not correspond to prices or quantities. Our theory includes parameter to measure marginal utility of quality units. This parametric approach also has the advantage of compactness in results presentation.
2. *The ratings are unreliable:* authors may have idiosyncratic tastes or be influenced by non-taste considerations.⁸ In order to minimize this concern, we use two completely independent sets of ratings, for which we have no reason to suspect that author-specific “specificities” would be correlated.
3. *The ratings are incomplete:* bad producers are usually omitted from the guidebooks and much wine is exported by non-producers. We try to correct for this by inferring the set of low quality firms and eliminating firms likely to have mixed quality.
4. *The ratings may influence price directly:* Some wine experts have become so famous worldwide, that their opinion exerts a direct impact on the price a firm can charge for its wine.
5. *The ratings may influence demand by increasing foreign customer awareness.* For instance, consumers in New Zealand are probably not aware of all varieties of red burgundy produced and available for consumption in France. A guide like Parker’s, because it is in English, and so widely popular will change to effective set of varieties in the consumer’s information set. To eliminate this concern, we run a separate set of regressions using only the French guide ratings (RVF) and restricting the sample to non-francophone markets (RVF is not translated).

⁸Parker and the Faiveley affair.

5 Results

We start by presenting results on our firm-level predictions about how quality affects the probability to become an exporter, quantity shipped and price charged.

5.1 Individual level analysis

Tables 7, 8, 9, and 10 report results of our firm-level regressions. In each of those tables, the first three columns average the two quality ratings (WBG and RVF) when measuring $s(i)$. The last three columns uses only the French rating (RVF) and restricts the sample to non-francophone countries.

Table 7: Champagne firm-level regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	$q_{jt}(i) > 0$	$\ln p_{jt}(i)$	$\ln q_{jt}(i)$	$q_{jt}(i) > 0$	$\ln p_{jt}(i)$	$\ln q_{jt}(i)$
$\ln s(i)$	3.61 ^a (0.03)	0.29 ^a (0.01)	1.80 ^a (0.03)	3.23 ^a (0.03)	0.25 ^a (0.01)	1.24 ^a (0.04)
constant		2.50 ^a (0.01)	6.22 ^a (0.03)		2.59 ^a (0.01)	6.87 ^a (0.03)
Ratings	WBG & RVF average			RVF only		
Destinations	all markets			non-francophone markets		
Observations	405189	12426	12426	317516	8801	8801
Within- jt R^2		0.117	0.203		0.092	0.102
ρ : frac. var. \sim FE		0.38	0.29		0.37	0.25

Destination-year (jt) fixed effects. Standard errors in parentheses.

Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

These regressions can be used to reveal the structural parameters of the model. Recall that equation (32) defines the elasticity of quantity with respect to quality as $\eta_{qs} \equiv (\gamma - \lambda)(\sigma - 1) - \lambda$. Therefore, the implied value of γ is $\lambda + (\eta_{qs} + \lambda)/(\sigma - 1)$. Parameter λ can be obtained as the coefficient on log quality in the price regression, 0.29. Anderson and van Wincoop (2004) report $5 \leq \sigma \leq 10$ as a reasonable range for the CES. Plugging in estimates obtained for the full sample, we infer γ to lie between 0.52 and 0.81. Using the higher of the two values, a consumer is willing to trade 3.7 bottles of low quality ($s = 1$) wine for one bottle of the highest quality ($s = 5$).

Furthermore, we can use estimates in Table 8 to test the Hallak (2006) assumption of income dependence of the preference for quality parameter, $\gamma_j = \gamma_0 + \gamma_1 \ln(y_j/y_0)$, where the income per capita of country j is normalized by the average world income (y_0). With this specification of preference for quality, the exported quantity equation becomes:

$$\ln q_j(i) = \ln[(\sigma - 1)/\sigma] - \sigma \ln \omega + \ln A_j + [(\gamma_0 - \lambda)(\sigma - 1) - \lambda] \ln s(i) + \gamma_1(\sigma - 1) \ln s(i) \ln(y_j/y_0). \quad (33)$$

Table 8: Champagne firm-level regressions with interactions

	(1)	(2)	(3)	(4)	(5)	(6)
	$q_{jt}(i) > 0$	$\ln p_{jt}(i)$	$\ln q_{jt}(i)$	$q_{jt}(i) > 0$	$\ln p_{jt}(i)$	$\ln q_{jt}(i)$
$\ln s(i)$	3.63 ^a (0.03)	0.31 ^a (0.01)	1.52 ^a (0.04)	3.21 ^a (0.03)	0.26 ^a (0.01)	0.83 ^a (0.04)
$\ln s(i) \times \ln(y_{jt}/y_0)$	0.15 ^a (0.02)	-0.03 ^a (0.01)	0.39 ^a (0.02)	0.13 ^a (0.02)	-0.02 ^b (0.01)	0.58 ^a (0.03)
Constant		2.49 ^a (0.01)	6.40 ^a (0.03)		2.59 ^a (0.01)	7.05 ^a (0.03)
Ratings	WBG & RVF average			RVF only		
Destinations	all markets			non-francophone markets		
Observations	366749	11809	11809	287070	8361	8361
Within- jt R^2		0.118	0.225		0.092	0.134
ρ : frac. var. \sim FE		0.39	0.25		0.37	0.23

Destination-year (jt) fixed effects. Standard errors in parentheses.

Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$.

$y_0 = \$6,800$ is the all-country average GDP per capita (1998–2003).

With estimates of $\lambda = 0.29$ from the price equation and $\sigma = 7$ from the literature, one can provide estimates of both γ_0 and γ_1 .

The interaction term coefficient in column (3) implies $\gamma_1 = 0.39/6 = 0.065$. A doubling of GDP per capita generates a 6.5% increase in the quality preference parameter.⁹ They also reveal $\gamma_0 = (1.81/6) + 0.29 = 0.6$. Finally, preference for quality parameter is revealed to be around two thirds for a country with the average income per capita ($y_0 = \$6,800$), while for the United States in 2003 it is $0.6 + 0.065 \times \ln(37658/6800) = 0.71$. Note also that the interaction coefficient should be zero for the price regression and almost is.

5.2 Conditional mean analysis

We now proceed to the conditional mean analysis that allow a discrimination between the QD and the ED models, based on certain contrasting predictions, in particular on how average prices and average quantities vary according to the popularity (N_j) and attractiveness (A_j) of each market.

The first set of relationships to examine are the relationships between conditional means and popularity shown in equations (14), (19), and (27). Since these are bivariate relationships, we can examine them directly using scatterplots of average quality, price, and quantity versus number of exporters. The quality sorting and efficiency sorting models both predict that all three relationships should be linear in log scale. Furthermore both

⁹Hallak (2006) reports a median estimate that implies $\gamma_1 = 0.03$ with the same assumption on $\sigma = 7$.

Table 9: Burgundy firm-level regressions

	(1) $q_{jt}(i) > 0$	(2) $\ln p_{jt}(i)$	(3) $\ln q_{jt}(i)$	(4) $q_{jt}(i) > 0$	(5) $\ln p_{jt}(i)$	(6) $\ln q_{jt}(i)$
$\ln s(i)$	1.69 ^a (0.02)	0.29 ^a (0.01)	0.58 ^a (0.03)	1.35 ^a (0.02)	0.19 ^a (0.01)	0.45 ^a (0.03)
constant		2.23 ^a (0.01)	6.23 ^a (0.02)		2.29 ^a (0.01)	6.34 ^a (0.03)
Ratings	WBG & RVF average			RVF only		
Destinations	all markets			non-francophone markets		
Observations	283362	11966	11966	226895	8516	8516
Within- jt R^2		0.066	0.037		0.034	0.029
ρ : frac. var. \sim FE		0.44	0.28		0.43	0.28

Destination-year (jt) fixed effects. Standard errors in parentheses.

Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

Table 10: Burgundy firm-level regressions with interactions

	(1) $q_{jt}(i) > 0$	(2) $\ln p_{jt}(i)$	(3) $\ln q_{jt}(i)$	(4) $q_{jt}(i) > 0$	(5) $\ln p_{jt}(i)$	(6) $\ln q_{jt}(i)$
$\ln s(i)$	1.96 ^a (0.04)	0.31 ^a (0.03)	0.40 ^a (0.06)	1.73 ^a (0.05)	0.24 ^a (0.04)	0.34 ^a (0.06)
$\ln s(i) \times \ln(y_{jt}/y_0)$	-0.25 ^a (0.03)	-0.02 (0.02)	0.14 ^a (0.04)	-0.35 ^a (0.03)	-0.04 (0.03)	0.09 ^b (0.04)
constant		2.23 ^a (0.01)	6.26 ^a (0.02)		2.28 ^a (0.01)	6.37 ^a (0.03)
Ratings	WBG & RVF average			RVF only		
Destinations	all markets			non-francophone markets		
Observations	254181	11789	11789	204338	8396	8396
Within- jt R^2		0.066	0.038		0.036	0.029
ρ : frac. var. \sim FE		0.45	0.27		0.45	0.28

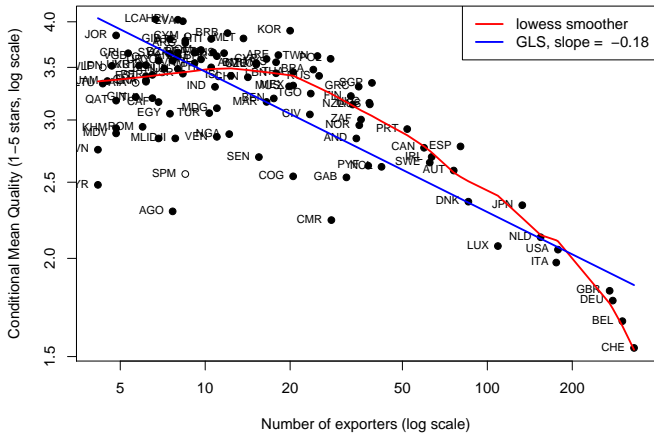
Destination-year (jt) fixed effects. Standard errors in parentheses.

Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

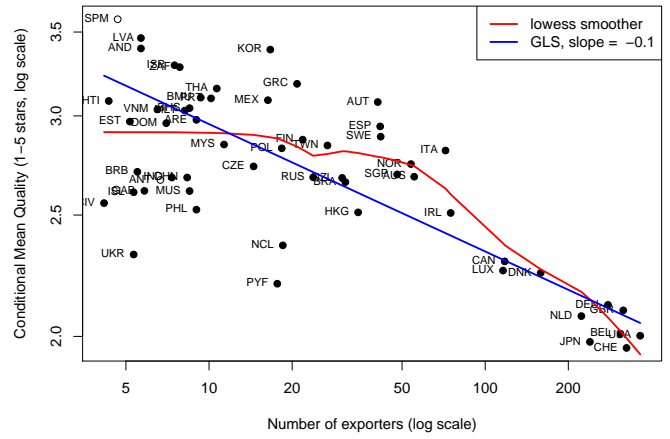
$y_0 = \$6,800$ is the all-country average GDP per capita (1998–2003).

Figure 4: Conditional mean graphs

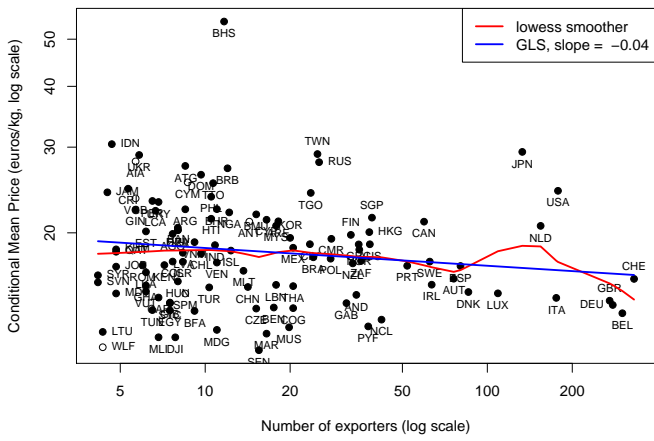
(a) quality, champagne



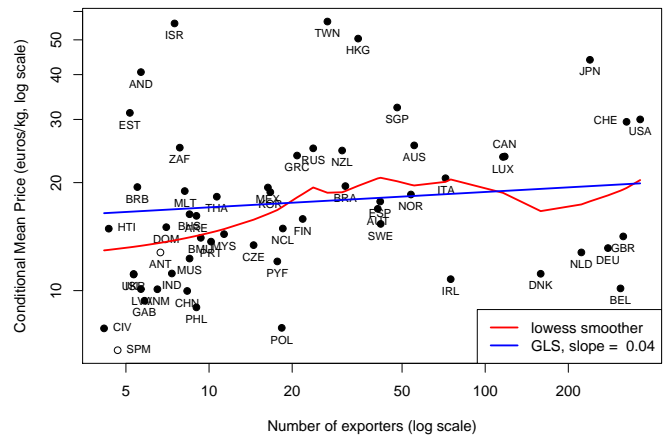
(b) quality, burgundy



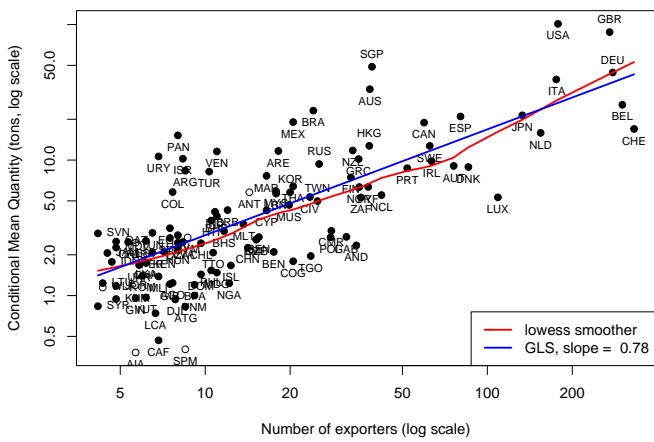
(c) price, champagne



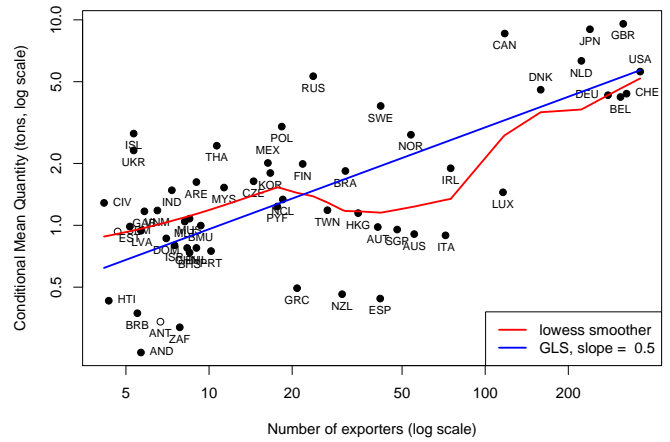
(d) price, burgundy



(e) quantity, champagne



(f) quantity, burgundy



models predict equal absolute slopes of opposite signs for the mean price and quantity figures. The quality sorting model alone predicts the negative average quality-popularity relationship, negative price-popularity relationship, and positive quantity-popularity relationship.

The six scatterplots shown as panels (a)–(f) of Figure 4 mainly support the quality supporting predictions. Average quality and popularity exhibit a strong negative relationships in panels (a) and (b)—once popularity is sufficiently high. Although the relationship is not globally linear, this may be due to small-sample issues for the less popular markets. On the other hand, average quantity and popularity have a strong positive relationship in panel (e) for champagne and a noisier, but still clearly positive relationship for red burgundy in panel (f). The mean price panels (c) and (d) are disappointing. The slope for red burgundy is close to zero and that for champagne is only mildly negative. Some very popular markets like Japan (JPN) have high prices that run counter to the model.

Tables 11 and 12 estimate the reduced form predictions based on equations (21) and (29). The quality sorting model predicts that any of the market primitives that raise attractiveness should lower average quality. They should have the same effect on price and the opposite sign effect on quantity. For champagne the results conform to priors remarkably well. Market size variables (population, income, high wine consumption) all raise popularity as predicted and *lower* average quality. Distance lowers popularity but raises quality. Speaking French (which is supposed to lower trade costs) raises popularity and lowers quality. Having high production of wine should reduce the price index in a market. This should reduce popularity and therefore raise quality. The signs are as expected although statistical significance is lacking. The performance for prices is disappointing as none of the size determinants enters significantly and all have small effects in absolute magnitude, something at odds with either theory. However, the trade cost determinants enter as the quality sorting model predicts. For quantity the quality sorting model is supported by the two main market size variables (population and income) as well as French. The results for burgundy shown in table 12 are a bit less consistent. However, for the most part they also support the quality sorting model. One perverse result is the positive and significant effect of per capita income in the price equation (column 3).

The reduced form version imposes some strong assumptions on A_j , in particular regarding the specification of trade costs and the determinants of demand for wine in importing countries. Another path is possible using our results from the firm-level regressions. Equation (32) reveals that the fixed effects estimated in the regression explaining individual export quantity corresponds to $\ln A_j$ in our model. One can retrieve those fixed effects, and estimate conditional mean regressions directly on $\ln A_j$, as theory suggests should be the case.

These bivariate relationships between means and imputed attractiveness are reported in Tables 13 and 14. The results once again offer much support for the quality sorting model. For both champagne and burgundy, popularity is more or less proportional to attractiveness. As predicted, average quality is negatively related to attractiveness. The

Table 11: Champagne, proxies for A_j

	(1)	(2)	(3)	(4)
	$\ln N_{jt}$	$\ln E [s(i)]$	$\ln E [p_{jt}(i)]$	$\ln E [q_{jt}(i)]$
\ln popn. (M_{jt})	0.40 ^a (0.05)	-0.07 ^a (0.01)	0.01 (0.01)	0.37 ^a (0.06)
\ln inc. p.c. (y_{jt})	0.76 ^a (0.06)	-0.05 ^a (0.01)	0.02 (0.02)	0.69 ^a (0.06)
\ln cons p.c (μ_{jt})	0.07 (0.05)	-0.04 ^a (0.01)	0.00 (0.01)	0.03 (0.05)
\ln prodn ($\searrow P_{jt}$)	-0.04 (0.03)	0.01 ^c (0.01)	-0.00 (0.01)	0.01 (0.03)
\ln distance ($\nearrow \tau_j$)	-0.03 (0.08)	0.07 ^a (0.02)	0.09 ^a (0.03)	0.10 (0.08)
French ($\searrow \tau_j$)	1.53 ^a (0.18)	-0.22 ^a (0.05)	-0.18 ^a (0.05)	0.61 ^a (0.14)
constant	-4.97 ^a (0.93)	1.17 ^a (0.26)	1.96 ^a (0.32)	0.67 (0.90)
Observations	168	160	168	168
R^2	0.654	0.529	0.212	0.741

GLS, $\text{weight}_j = \sqrt{N_j}$, Standard errors in parentheses
Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

Table 12: Burgundy, proxies for A_j

	(1)	(2)	(3)	(4)
	$\ln N_{jt}$	$\ln E [s(i)]$	$\ln E [p_{jt}(i)]$	$\ln E [q_{jt}(i)]$
\ln popn. (M_{jt})	0.56 ^a (0.07)	-0.05 ^a (0.01)	-0.02 (0.03)	0.39 ^a (0.05)
\ln inc. p.c. (y_{jt})	1.15 ^a (0.07)	-0.03 (0.02)	0.24 ^a (0.03)	0.49 ^a (0.06)
\ln cons p.c. (μ_{jt})	0.03 (0.07)	-0.02 (0.01)	-0.08 ^b (0.03)	-0.01 (0.05)
\ln prodn ($\searrow P_{jt}$)	-0.10 ^b (0.04)	0.01 ^b (0.01)	0.05 ^a (0.01)	-0.10 ^a (0.02)
\ln distance ($\nearrow \tau_j$)	0.01 (0.13)	0.00 (0.02)	0.19 ^a (0.05)	-0.12 ^c (0.07)
French ($\searrow \tau_j$)	1.32 ^a (0.22)	-0.18 ^a (0.04)	0.10 (0.12)	0.59 ^a (0.18)
Constant	-9.42 ^a (1.36)	1.36 ^a (0.31)	-0.64 (0.54)	3.21 ^a (0.98)
Observations	148	112	148	148
R^2	0.688	0.235	0.451	0.639

GLS, $\text{weight}_j = \sqrt{N_j}$, Standard errors in parentheses
Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

Table 13: Champagne, FE estimate for A_j

	(1)	(2)	(3)	(4)
	$\ln N_{jt}$	$\ln E [s(i)]$	$\ln E [p_{jt}(i)]$	$\ln E [q_{jt}(i)]$
$\ln A_{jt}$	0.97 ^a (0.09)	-0.17 ^a (0.02)	-0.07 ^b (0.03)	1.18 ^a (0.04)
Constant	3.02 ^a (0.15)	0.94 ^a (0.03)	2.86 ^a (0.03)	9.18 ^a (0.06)
Observations	176	176	176	176
R^2	0.432	0.470	0.072	0.808

GLS, $\text{weight}_j = \sqrt{N_j}$, Standard errors in parentheses
Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

Table 14: Burgundy, FE estimate for A_j

	(1)	(2)	(3)	(4)
	$\ln N_{jt}$	$\ln E [s(i)]$	$\ln E [p_{jt}(i)]$	$\ln E [q_{jt}(i)]$
$\ln A_{jt}$	0.89 ^a (0.20)	-0.12 ^a (0.02)	-0.04 (0.10)	1.20 ^a (0.07)
Constant	2.16 ^a (0.25)	0.87 ^a (0.02)	2.83 ^a (0.09)	7.87 ^a (0.08)
Observations	124	124	124	124
R^2	0.186	0.201	0.003	0.723

GLS, $\text{weight}_j = \sqrt{N_j}$, Standard errors in parentheses
Significance levels: ^c $p < 0.1$, ^b $p < 0.05$, ^a $p < 0.01$

sign on the price effect is supportive of quality sorting but it is only statistically significant for champagne. Finally the quantity relationships are strongly significant. Indeed the result is too strong to be consistent with the theory's prediction that the price and quantity effects be equal in absolute value. The asymmetry in magnitudes we find is also at odds with the efficiency sorting model. Taken together with the previous results, it seems to us that the prices are highly noisy and appear to be driven by forces outside the basic models. Noise in unit values is to be expected but perhaps greater predictive power would be possible in a model with some pricing to market. The Dixit-Stiglitz-Krugman prediction of destination-invariant FOB prices seems hard to square with the results.

6 Conclusion

We have illustrated the importance of quality for trade by examining an industry in which quality can be measured (albeit imperfectly). Heterogeneous firms theory implies a threshold quality for market entry. The result is quality sorting: good firms are better able to serve difficult markets. We show firms with higher measured quality are more likely to export, export more, and charge higher prices. Champagne and (to a lesser extent) red burgundy exhibit quality sorting using direct measures. Quantities also respond to market attractiveness with the predicted sign. Firm-level prices exhibit much destination level variation that is not predicted by the model. Average prices do not exhibit quality sorting.

7 References

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A Mean quality: other distributions

We can calculate expected quality with exponential and uniform draws for s . For $G(s) = 1 - \exp(-\kappa s)$ we have

$$\mathbb{E}[s \mid s > \hat{s}] = \hat{s} + 1/\kappa. \quad (34)$$

Substituting N_j/N_x in place of \hat{s} using the inverse CDF, we obtain

$$\mathbb{E}[s \mid s > \hat{s}] = \frac{\ln N_x - \ln N_j}{\kappa}. \quad (35)$$

For $G(s) = (s - \underline{s})/(\bar{s} - \underline{s})$, we have

$$\mathbb{E}[s \mid s > \hat{s}] = (\bar{s} + \hat{s})/2 \quad (36)$$

Substituting N_j/N_x in place of \hat{s} using the inverse CDF, we obtain

$$\mathbb{E}[s \mid s > \hat{s}] = \bar{s} - \frac{(\bar{s} - \underline{s})N_j}{2N_x}. \quad (37)$$

Thus we see truncated average quality can take various functional forms with respect to N_j . However, the general result is that average quality declines with N_j , and thus with in attractiveness of the market (A_j). The effect is stronger when there is greater dispersion in the quality draws: i.e. high $\bar{s} - \underline{s}$ or low κ .