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Does quality pay off? "Superstar" wines and the uncertain price premium across quality grades

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Abstract

We use data from Wine Spectator on 266,301 bottles from 12 countries sold in the United States to investigate the link between the score awarded by the guide and the price charged. In line with the literature, the link between quality and price is positive. In a deeper inspection, however, hedonic regressions show that the price premium attached to higher quality is significant only for "superstar" wines with more than 90 points (in a 50-100 scale), while prices of wines between 50 and 90 points are not statistically different from each other. Furthermore, an analysis performed through normal heteroskedastic and quantile regression models shows that the dispersion of quality-adjusted prices is described by an asymmetric U-shaped function of the score; that is, products with the lowest and highest quality have the highest residual standard deviation. Pursuing excellence is a risky strategy: the average price is significantly higher only for wines that achieve top scores, and the price premium becomes more volatile.

Keywords: Wine, price, quality.

JEL codes: L11, Q11, L66.

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1. Introduction

Over the last four decades the wine sector has undergone major structural changes that have made it a highly globalised and competitive market. On the supply side, firms from non-traditionally wine-producing countries entered the market with growing quantities, rising quality and competitive prices (Bartlett, 2009; Castriota, 2020). On the demand side, per-capita wine consumption in traditional producing countries (i.e. Southern Europe) has been declining, and consumers in general have become more attentive to quality, price and other external cues (Rebelo et al., 2019). As a result, competition in the wine market has never been higher.

When buying wine, consumers face a much more complicated situation than for any other product they can purchase: the horizontal and vertical product differentiation is huge, and the differences between products are so specific that the average inexperienced consumer feels disoriented. Furthermore, it is widely accepted that wine is an "experience good" (Cardebat, 2017, p. 32; Thornton, 2013, p. 38), as its quality cannot be assessed before consumption, and to some extent a "credence good", as its quality is difficult to assess for inexperienced consumers even after consumption (Ashton, 2014; Goldstein et al., 2018; Gottschalk, 2018). With such information asymmetries between producers and consumers, the latter often make their choices based on various kinds of signals such as price, firm reputation and assessed product quality.

In this context, wine guides have assumed the role of rating agencies (Hay, 2010) and play an increasingly important role in supporting consumers' choices, especially since the spread of the internet, with its new communication technologies and distribution channels. Every year, an increasing number of wine guidebooks and other consumer reports are published and used by a large audience (Chossat and Gergaud, 2003). In addition to supporting consumers' choices, guides represent an essential tool for producers to certify and communicate the quality of their products (Schnabel and Storchmann, 2010). Since achieving high quality is commonly the result of significant investments and targeted entrepreneurial strategies, the question arises whether there is a correspondence between the efforts to achieve quality – as proxied by the guide score – and the price of a bottle of wine.

Indeed, an extensive literature has found a significant positive correlation between the quality assigned by expert wine critics and price (see, among others, Ali, Lecocq and Visser, 2018; Ashton, 2016; Dubois and Nauges, 2010; Ferro and Benito Amaro, 2018;

Gibbs et al., 2009; Masset et al., 2015). However, other researches argue that the correlation between price and quality reported in the guides is weak, and quality explains only a minor fraction of the price (Ali and Nauges, 2007; Ashton, 2014; Cardebat et al., 2018). Recent contributions suggest that hedonic functions that consider market segmentation can better explain the variability of the data and provide better estimates of the relationships among wine attributes and prices (Amédée-Manesme et al., 2020; Cacchiarelli et al., 2014; Caracciolo et al., 2016; Caracciolo and Furno, 2020; Costanigro et al., 2007). In this regard, Costanigro et al. (2007) segment 13,024 Wine Spectator reviews for California and Washington red wines into wine classes based on price ranges and find that the positive correlation between scores and price is more relevant as the price range increases. In contrast, Amédée-Manesme et al. (2020) applied quantile regressions with market segmentation based on price on 50,426 transactions for the five first growths of Bordeaux. Although they find that the effect of wine characteristics on selling price can be better explained by estimating quantile regressions across price categories, they find that the Parker scores impact on prices is homogeneous and almost constant for the price classes.

Next, several empirical studies have examined the association between price and quality by focusing on price dispersion (Ashton, 2014; Cardebat et al., 2017; Jaeger and Storchmann, 2011), finding that wine price exhibits a significant variability even among very similar products (Coppola, Sodano, & Verneau, 2001). Jaeger and Storchmann (2011) examine whether quality explains the observed retail price dispersion after controlling for location differences and find a positive relationship, although weak, between price levels and price dispersion.

In this work, we deepen and clarify the relationship between the assessed quality and wine price using a large database of 266,301 reviews published by Wine Spectator. First, we estimate a hedonic price regression where we control for quality and other variables. Results show that prices are statistically higher only when wines received well above 90 points, the range of scores being 50-100. Only "superstar" wines benefit large and growing price premia, while all other wines have similar prices. Then, we use a normal heteroskedastic model and a quantile regression model to account for the possibility that the dispersion of price is not constant across values of the quality score. The relationship between the dispersion of price residuals and quality is U-shaped; that is, dispersion is higher with very low and very high ratings. Not only the price premium attached to higher quality grows exponentially rather than linearly, but it is also more volatile with the lowest/highest ratings. This implies two sources of uncertainty for winemakers. The first refers to the quality achieved with given levels of investments (e.g. in agricultural and oenological equipment and treatments). The second has to do with the price a bottle of a certain quality will be charged. Trying to produce top wines to obtain very high prices is risky since there is no automatic rule to obtain 94 instead of 90 points; furthermore, in the favourable scenario where the wine becomes a "superstar", the dispersion of residuals becomes larger.

The paper is organised as follows: the next section introduces the database and the source, Wine Spectator. Then, section 3 presents the results of the empirical analysis divided into subsections for the different regression models. Finally, conclusions are presented in Section 4.

2. Database

The source of the data analysed in this paper is Wine Spectator (WS). With a history of 40 years and more than 3 million readers, the WS lifestyle magazine is considered among the most prestigious authorities in the oenological sector and a reference point for many consumers worldwide (Chen, Velchev, Palmer, and Atkison, 2018). Relying on a team of over fifteen experienced tasters and blind tasting sessions in controlled environments, WS has provided over 380,000 wine ratings and sensory reviews available by subscription on the website.

Each review includes two main sections. The first section provides information about the wine and the producer, like vintage, country and region of origin, the price for a bottle and bottle size. Furthermore, the publication date indicates the period of market availability of the wine and its age at release. The second section consists of the score summary of the overall quality of a wine and the tasting notes describing its style and character. The WS scoring is based on a rating within a 100-point scale and reflects how highly the reviewer regards the wine's potential quality relative to other wines in the same category. WS recommendations on how to interpret its scores are as follows:

95–100, Classic: a great wine;

90–94, Outstanding: a wine of superior character and style;

85–89, Very good: a wine with special qualities;

80–84, Good: a solid, well-made wine;

75–79, Mediocre: a drinkable wine that may have minor flaws;

50–74, Not Recommended.

For this research, we have collected the ratings delivered from 1984 to 2019 of wines produced in Argentina, Australia, Canada, Chile, France, Germany, Italy, New Zealand, Portugal, South Africa, Spain, USA. For the sake of consistency, we limited the analysis to 750 mL bottles and excluded bigger and smaller formats.

3. Empirical analysis

3.1 Descriptive statistics

Table 1 provides a description of the variables and the summary statistics. In the empirical analysis, we will rely on the real price in constant 2019 terms, ranging between 5 and 5,487 $, with an average of 49. Wine quality is measured by a score between 50 and 100, with a mean of 87. In addition to the vintage and year of issue, we have data on horizontal differentiation – whether the wine is ready to drink and the type of wine – and on the collective reputation of the wine appellation. This latter information is available only for France and Italy and comes from the Hugh Johnson wine guide, which has been published since 1977. Table A1 in the Appendix presents the distribution of wines by country. Since Wine Spectator is an American guide, it is understandable that 31.8% of bottles rated are from the United States. France and Italy are the second and third countries with 24.2% and 17.3%. The remaining countries have minor shares, with Canada having a symbolic 0.1% presence.

Figure 1 shows the average real price by score value. Average real prices look flat and grow exponentially once the score exceeds 90 points. Regressing average real prices over a cubic trend provides an R^2 equal to 0.86. Figures A1 and A2 show the actual and normal distribution of score values and the natural logarithm of the real price, which will be used in the econometric analysis. Few bottles get less than 70 and more than 98 points.

3.2 OLS hedonic regressions

The empirical analysis relies on hedonic price regressions. In Table 2, which uses the full database with all countries, the natural logarithm of the real price is regressed over the variables listed in Table 1. Regressions include the vintage year and country dummy variables that are not shown for space reasons but are available upon request. Standard errors are clustered at the country level. We start with a regression that does not include the quality score (column 1), then add the score in its linear (column 2), quadratic (column 3) and cubic (column 4) specifications, while the last regression uses a set of dummy variables for each score value (column 5).

Quality is always strongly significant in all the specifications. The R^2 from column 5, which includes DVs for all the score values and is the most complete of the regressions proposed, is very close to that of column 4, which uses a simple cubic function. The coefficients of the DVs of column 5 are not shown for reasons of space but are available upon request; Figure 2 plots the value of the coefficients with their confidence intervals. The coefficients of the DVs for scores from 50 to 90 are not statistically different. Above 90 points, the effect of quality on price grows exponentially and the coefficients of the DVs become gradually higher than those from 50 to 90 points at a 95% significance level.

In line with previous literature, we find a positive effect of quality on price. However, descriptive statistics and econometric evidence show that the price premium attached to quality is concentrated in the upper end of the distribution. On average, the prices of wines with scores between 50 and 90 points are statistically not different.

3.3 Heteroskedastic hedonic regressions

In order to describe potential nonlinear effects, we adopt a flexible approach: we repeat the hedonic regressions by describing the association with the score, vintage year, and age with restricted cubic splines with two internal knots at score = (85, 90), year = (2000, 2011), and age = (5, 10). With the above definition, the design matrix $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n)\mathbf{T}$ is composed of 26 columns: the constant term, four indicators of Dessert, Red, Rosé, and Sparkling wine (reference = White), the “drinknow” indicator, eleven country dummy variables (reference = Argentina), and the three-dimensional splines associated with the score, vintage year, and age. The mean regression model, i.e., the standard "linear" model with constant variance largely used in the literature (see Castriota, 2020, Ch.2 for a review of empirical studies of wine quality and price), was not optimal since it was immediately evident the presence of data heteroskedasticity. Therefore, we considered two alternative solutions: either a Normal heteroskedastic model or a quantile regression approach.

The Normal heteroskedastic model is the natural generalisation of the standard normal model, i.e., the "linear" (mean) regression model. The idea is to describe by a function of the predictors not only the mean but also the variance of a Normal distribution, such that $Y \sim N(\mu(\mathbf{x} \mid \boldsymbol{\beta}), \sigma^2(\mathbf{x} \mid \boldsymbol{\theta}))$. We defined

$$\mu(\mathbf{x} \mid \boldsymbol{\beta}) = \mathbf{x}^T\boldsymbol{\beta}, \qquad \log\{\sigma^2(\mathbf{x} \mid \boldsymbol{\theta})\} = \mathbf{x}^T\boldsymbol{\theta}.$$

This modelling approach allows to directly account for the presence of heteroskedasticity. The conditional mean is given by $\mathbf{x}^T\boldsymbol{\beta}$, which is also the value of the median. Other quantiles, for example the quartiles or the deciles, are defined as $Q(p \mid \mathbf{x}, \boldsymbol{\beta}, \boldsymbol{\theta}) = \mu(\mathbf{x} \mid \boldsymbol{\beta}) + \sigma(\mathbf{x} \mid \boldsymbol{\theta})z(p)$, where z(.) is the quantile function of a N(0,1) distribution. With our specification of the design matrix, the model had 26 + 26 = 52 parameters, that were estimated by maximum likelihood. Standard errors were computed by applying standard asymptotic theory, i.e., by using the square root of the diagonal elements of the negative inverse of the Hessian matrix of the log-likelihood, evaluated at its maximum.

Results in Figure 3 show the predicted mean and median, the quartiles, and the 5^{th} and 95^{th} percentiles of ln(price), as a function of the quality score. All functionals are approximately J-shaped or U-shaped, with all quantiles increasing rapidly for scores above 85. Interestingly, also dispersion parameters show a U-shaped association with the score. In Figure 5, we report the difference between the estimated 95^{th} and 5^{th} percentile, that achieves a global minimum at approximately 87.5 points.

3.4 Quantile hedonic regressions

In the Normal model, specific quantiles of interest can only be extrapolated using the assumed parametric distribution. An alternative approach is to apply a quantile regression model (e.g., Koenker, 2005). This method avoids global parametric assumptions and allows to directly describe how the p-th quantile depends on the observed predictors, using a regression model of the form

$$Q(p \mid \mathbf{x}, \boldsymbol{\beta}) = \mathbf{x}^T\boldsymbol{\beta}(p).$$

In this model, $\boldsymbol{\beta}(p)$ is a quantile-dependent vector of regression coefficients. For example, the coefficients that describe the conditional median ($p = 0.5$) differ from those that characterise the first quartile ($p = 0.25$) or the 95th percentile ($p = 0.95$).

Estimation is carried out by minimising a loss function

$$L(\boldsymbol{\beta}) = \Sigma_i(p - u_i)(y_i - \mathbf{x}_i^T\boldsymbol{\beta}(p))$$

where $u = I(y \leq \mathbf{x}^T\boldsymbol{\beta}(p))$ (e.g., Koenker, 2005), while standard errors can be computed by using nonparametric bootstrap. In our analysis, we estimated quantiles of order $p = \{0.05, 0.25, 0.5, 0.75, 0.95\}$. Results are illustrated in Figure 4 and are very similar to those obtained with the Normal heteroskedastic model. Some minor differences can be obtained in the estimated 5th and 95th percentiles, especially for low values of the quality score. This may suggest that the tails are not well represented by a Normal distribution. In Figure 5, we can also see that the difference between the 95th and the 5th percentile found with quantile regression deviates slightly from that obtained using the Normal heteroskedastic model.

4. Conclusions

Quality is commonly considered the most important driver of wine prices. An extensive literature has shown the positive link between the two variables. This work provides new evidence using an extensive database on 266,301 bottles from 12 countries sold in the United States and rated by Wine Spectator. The positive link between quality and price achieved is confirmed. However, the focus on "superstar" wines deserves more attention. In fact, whereas wines with quality scores between 50 and 90 points (in a 50-100 range) have prices that are statistically not different, above 90 points prices grow exponentially and become statistically different. Furthermore, the dispersion of the residuals of hedonic regressions is U-shaped with respect to quality.

While many wine producers pursue quality excellence to obtain greater recognition on the market and a premium on the retail price, the significant effect of wine quality on prices is only achieved with outstanding scores. Hence it seems reasonable to wonder whether the potential benefits in terms of price are worth the efforts and the costs required to achieve an excellent quality product. This research suggests that a strategy to attain a higher price based on quality can be effective when the aim is to produce outstanding wine, i.e. with a quality score higher than 90, beyond which the prices increase considerably.

On the other hand, wines with a quality score above 90 also show a significantly higher price dispersion, suggesting that if producing wines of excellent quality can bring significant benefits in terms of price, at the same time also increases the uncertainty about the results. Pursuing an outstanding quality is a very ambitious and potentially profitable strategy, but it also exposes greater risks due to price dispersion.

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Table 1: Description of the variables and summary statistics

Variable	Description	Obs	Mean	Std. Dev.	Min	Max
Price	Nominal price	266,301	40.15	54.23	5	5,000
Real price	Real price in 2019 terms	266,301	49.24	63.62	5.21	5,487
Score	Score (measure of quality)	266,301	87.00	4.23	50	100
Vintage	Vintage (year of harvest)	266,301	2005	7.02	1827	2017
Age	Age of the wine (years)	266,301	2.78	1.96	0	172
Drink after	Wine which is better to drink after some time	266,301	0.20	0.40	0	1
Drink now	Wine which is ready to drink now	266,301	0.71	0.45	0	1
Dessert	Sweet wine	266,301	0.01	0.08	0	1
Red	Red wine	266,301	0.70	0.46	0	1
Rosé	Rosé wine	266,301	0.01	0.09	0	1
White	White wine	266,301	0.28	0.45	0	1
Sparkling	Sparkling wine	266,301	0.01	0.08	0	1
Collective reputation	Collective reputation by Hugh Johnson's wine guide	110,562	1.94	1.34	0	4.5

Table 2: First stage, determinants of ln of real wine price, all countries

Variables	(1)	(2)	(3)	(4)	(5)
Age	0.120***	0.0736***	0.0602**	0.0591**	0.0587**
	(0.0109)	(0.0157)	(0.0195)	(0.0198)	(0.0201)
Dessert	0.370	0.277	0.250	0.241	0.248
	(0.236)	(0.157)	(0.146)	(0.143)	(0.145)
Red	0.140	0.109	0.116	0.118	0.116
	(0.145)	(0.130)	(0.120)	(0.118)	(0.117)
Rose	-0.367***	-0.228***	-0.214***	-0.220***	-0.214**
	(0.115)	(0.0686)	(0.0670)	(0.0703)	(0.0713)
Sparkling	-0.0669	0.0238	0.0467	0.0503	0.0503
	(0.123)	(0.0688)	(0.0595)	(0.0575)	(0.0548)
Drink now	-0.173	-0.241**	-0.154*	-0.136	-0.135
	(0.102)	(0.0990)	(0.0825)	(0.0761)	(0.0819)
Score		0.0811***	-0.762***	1.637***	
		(0.00577)	(0.108)	(0.478)	
Score2			0.00496***	-0.0246***	
			(0.000649)	(0.00637)	
Score3				0.000120***	
				(2.83e-05)	
Constant	-13.97***	-13.61***	23.91***	-40.51***	-5.194
	(1.874)	(2.552)	(7.499)	(10.59)	(3.355)
Score DVs	No	No	No	No	Yes
Observations	266,301	266,301	266,301	266,301	266,301
R-squared	0.194	0.373	0.422	0.427	0.429

Notes: Regressions include vintage and country DVs. Robust standard errors clustered at the country level in parentheses. Regression in column 5 uses a set of dummy variables for each score value instead of the linear, quadratic or cubic functions (results are omitted for reasons of space but are available upon request and are visually represented in Figure 2).
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Average real price in $ and quality score

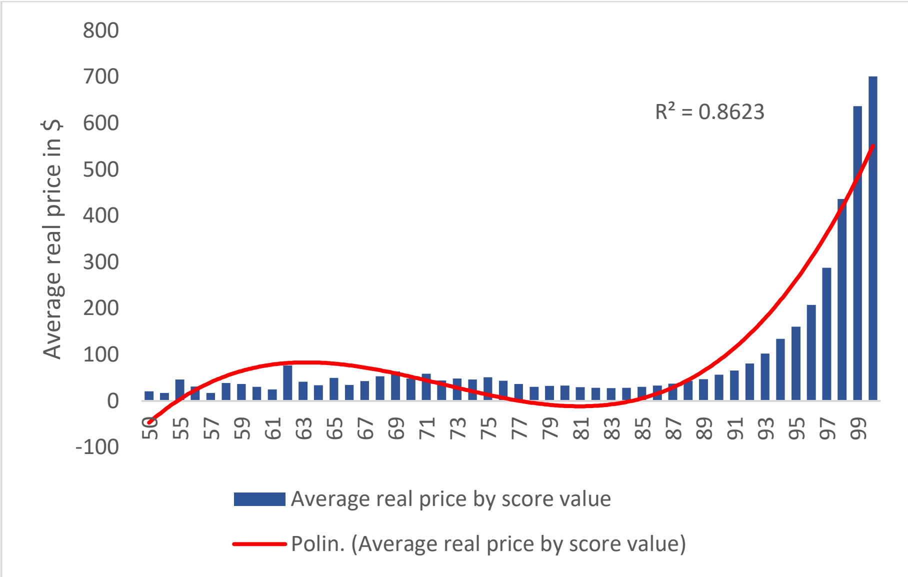
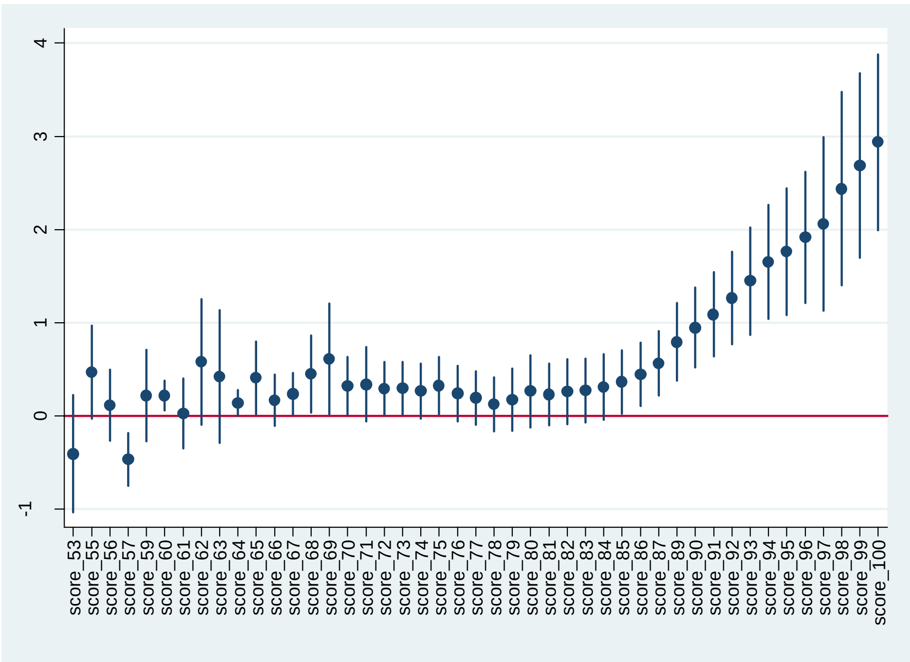
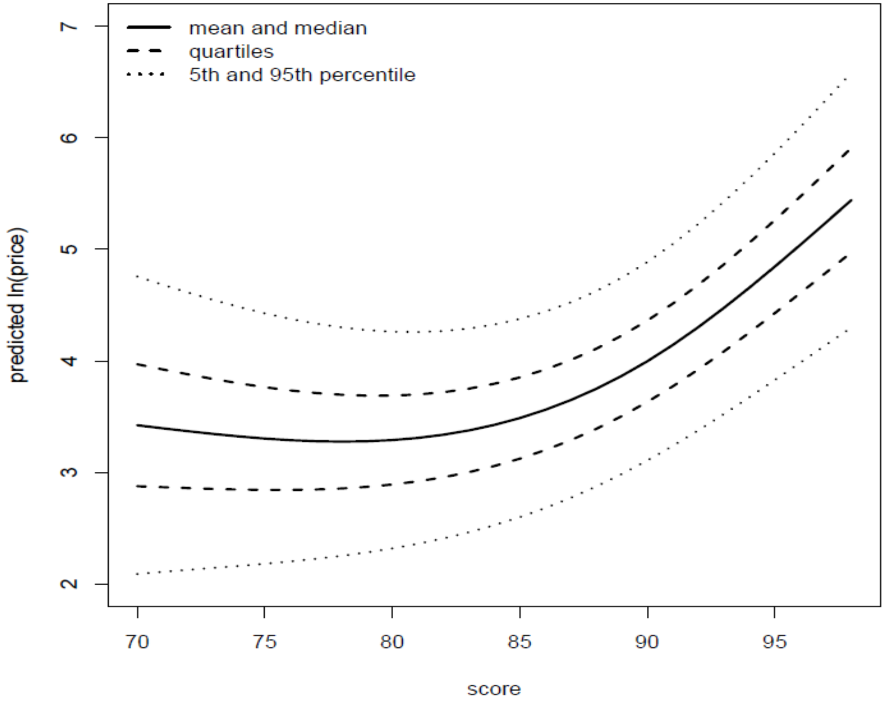


Figure 2: Coefficients and 95% c.i. of the score DVs



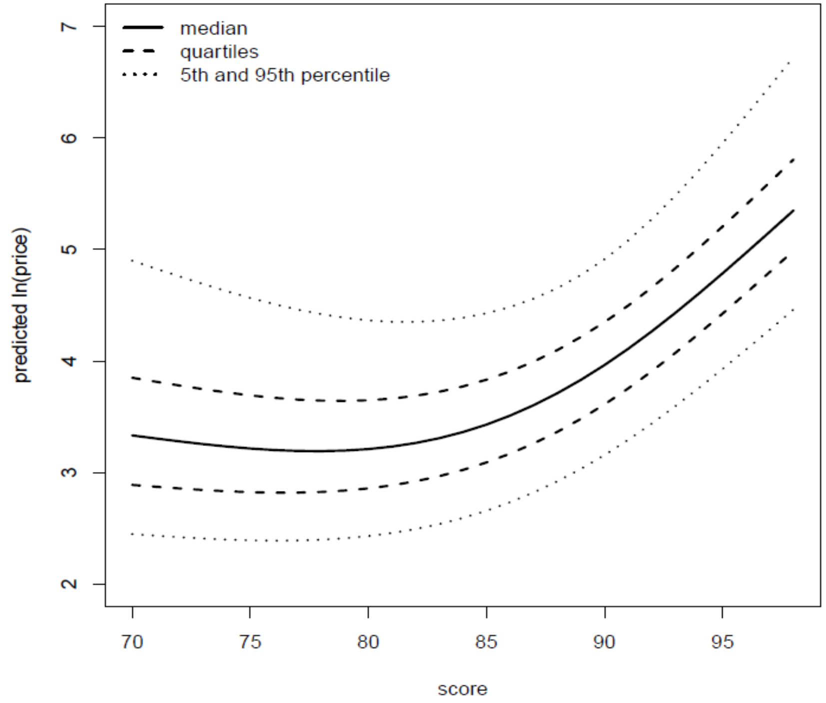
Note: Results come from regression 5 in Table 3.

Figure 3: Normal heteroskedastic model



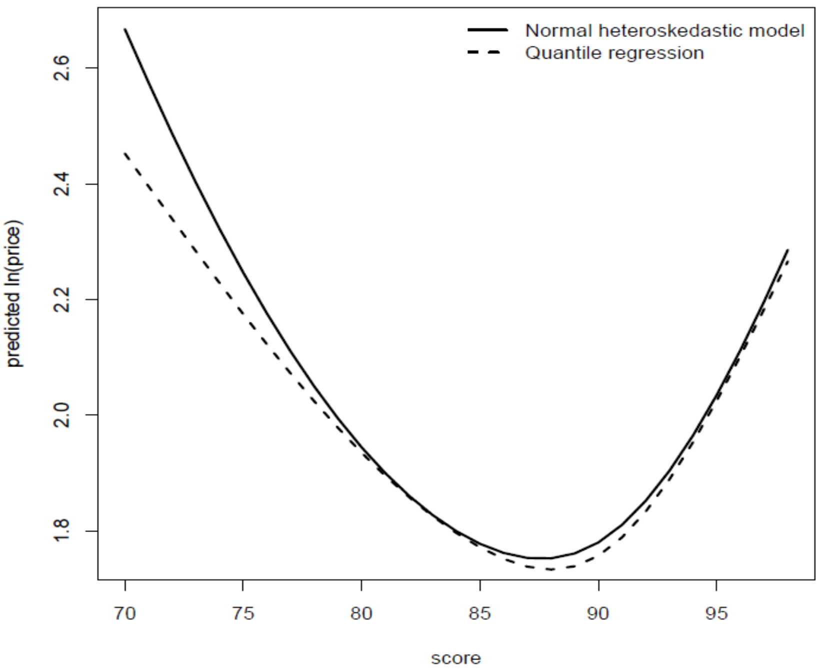
Predicted mean and median, quartiles, and 5th and 95th percentiles of ln(price), as a function of the quality score, as estimated by applying a Normal heteroskedastic model.

Figure 4: Quantile regression model



Predicted mean and median, quartiles, and 5th and 95th percentiles of ln(price), as a function of the quality score, as estimated by applying a Quantile regression model.

Figure 5: Difference between Q(0.95) and Q(0.05)



Estimated difference between the 95th and the 5th percentile of ln(price), expressed as a function of the quality score. Continuous line: Normal heteroskedastic model. Dashed line: quantile regression model.

Table A1: Sample distribution by country

Country	Freq.	Percent	Cumulative
USA	84,547	31.8	31.8
France	64,414	24.2	55.9
Italy	46,148	17.3	73.3
Spain	15,882	6.0	79.2
Australia	13,522	5.1	84.3
Germany	10,101	3.8	88.1
Chile	7,125	2.7	90.8
Argentina	6,924	2.6	93.4
South Africa	6,348	2.4	95.8
New Zealand	5,589	2.1	97.9
Portugal	5,356	2.0	99.9
Canada	345	0.1	100.0
Total	**266,301**	**100**	**100**

Table A2a: First stage, determinants of ln of real wine price, by country

Variables	(1) Italy	(2) France	(3) Germany	(4) Spain	(5) Portugal	(6) Argentina	(7) Australia	(8) Canada	(9) Chile	(10) New Zealand	(11) South Africa	(12) USA
Age	0.0113***	0.0262***	0.0889***	0.0865***	0.0233***	0.195***	0.129***	0.222***	0.169***	0.189***	0.126***	0.109***
	(0.00187)	(0.00246)	(0.0173)	(0.00285)	(0.00401)	(0.00554)	(0.00609)	(0.0269)	(0.00676)	(0.00705)	(0.00508)	(0.00186)
Dessert	-0.00372	0.0450	1.402***	0.303**	0.375***	-0.0211	0.144	0.290*	-0.0714	-0.0635	-0.0464	0.0222
	(0.0213)	(0.0690)	(0.0525)	(0.122)	(0.0312)	(0.113)	(0.140)	(0.160)	(0.277)	(0.0680)	(0.0570)	(0.0596)
Red	0.0689***	-0.180***	0.540***	0.0332***	0.151***	-0.0408***	0.137***	0.195***	-0.00177	0.245***	0.0534***	0.302***
	(0.00887)	(0.00538)	(0.0607)	(0.0105)	(0.0175)	(0.0115)	(0.0106)	(0.0507)	(0.0102)	(0.0120)	(0.0114)	(0.00385)
Rose	-0.0241	-0.582***		-0.231***	-0.0580	0.0743**	0.0357		0.0722***	-0.0698	0.0173	-0.148***
	(0.0455)	(0.0398)		(0.0158)	(0.0413)	(0.0297)	(0.0389)		(0.0256)	(0.0506)	(0.0244)	(0.0102)
Sparkling	-0.126***	0.234**	0.230**	0.0970***	0.185***	0.194***	0.0762		0.521***	-0.0955**	0.0792	0.0830***
	(0.0268)	(0.104)	(0.107)	(0.0228)	(0.0646)	(0.0693)	(0.0581)		(0.0955)	(0.0477)	(0.0544)	(0.0137)
Drink now	0.0659***	-0.290***	-0.0931***	-0.193***	-0.258***	0.0203	-0.208***	-0.0705	-0.0388*	-0.150***	-0.0699***	-0.175***
	(0.00588)	(0.00515)	(0.0117)	(0.0159)	(0.0244)	(0.0258)	(0.0116)	(0.0855)	(0.0216)	(0.0236)	(0.0250)	(0.00471)
Score	0.320	2.039***	0.809***	2.184***	-1.001	4.332***	1.734**	8.124	2.044***	5.642***	2.790***	0.281**
	(0.641)	(0.111)	(0.203)	(0.232)	(0.646)	(0.345)	(0.881)	(5.042)	(0.392)	(0.776)	(0.246)	(0.116)
Score2	-0.0107	-0.0298***	-0.0128***	-0.0311***	0.00870	-0.0598***	-0.0286***	-0.102*	-0.0307***	-0.0714***	-0.0397***	-0.00579***
	(0.00759)	(0.00136)	(0.00256)	(0.00295)	(0.00770)	(0.00433)	(0.0104)	(0.0601)	(0.00488)	(0.00924)	(0.00317)	(0.00141)
Score3	7.20e-05**	0.000143***	6.60e-05***	0.000148***	-1.77e-05	0.000272***	0.000147***	0.000423*	0.000150***	0.000300***	0.000186***	3.54e-05***
	(2.99e-05)	(5.57e-06)	(1.07e-05)	(1.24e-05)	(3.06e-05)	(1.81e-05)	(4.05e-05)	(0.000239)	(2.02e-05)	(3.66e-05)	(1.35e-05)	(5.66e-06)
Constant	8.154	-45.74***	-14.08***	-50.69***	33.87*	-101.3***	-28.31	-214.1	-41.69***	-145.4***	-62.00***	-0.824
	(17.97)	(3.004)	(5.337)	(6.078)	(18.04)	(9.091)	(24.97)	(140.8)	(10.49)	(21.71)	(6.346)	(3.204)
Region DVs	No	No	No	No	No	No	No	No	No	No	No	No
Observations	46,148	64,414	10,101	15,882	5,356	6,924	13,522	345	7,125	5,589	6,348	84,547
R-squared	0.333	0.453	0.440	0.489	0.580	0.610	0.493	0.545	0.579	0.450	0.603	0.413

Notes: Regressions include vintage and country DVs. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A2b: First stage, determinants of ln of real wine price, by country

Variables	(13) Italy	(14) France
Age	0.0156***	0.0253***
	(0.00196)	(0.00224)
Dessert	-0.115***	0.454***
	(0.0216)	(0.0659)
Red	-0.0439***	0.0595***
	(0.00965)	(0.00602)
Rose	-0.00655	-0.0329
	(0.0425)	(0.0330)
Sparkling	-0.0500*	0.0617
	(0.0299)	(0.0791)
Drink now	0.0631***	-0.0773***
	(0.00631)	(0.00480)
Score	0.248	2.488***
	(0.626)	(0.0982)
Score2	-0.00955	-0.0350***
	(0.00741)	(0.00121)
Score3	6.61e-05**	0.000163***
	(2.92e-05)	(4.98e-06)
Collective reputation	0.0239***	0.107***
	(0.00245)	(0.00242)
Constant	9.205	-58.18***
	(17.55)	(2.645)
Region DVs	Yes	Yes
Observations	46,148	64,414
R-squared	0.359	0.638

Notes: Regressions include vintage and country DVs. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Figure A1: Distribution of score values

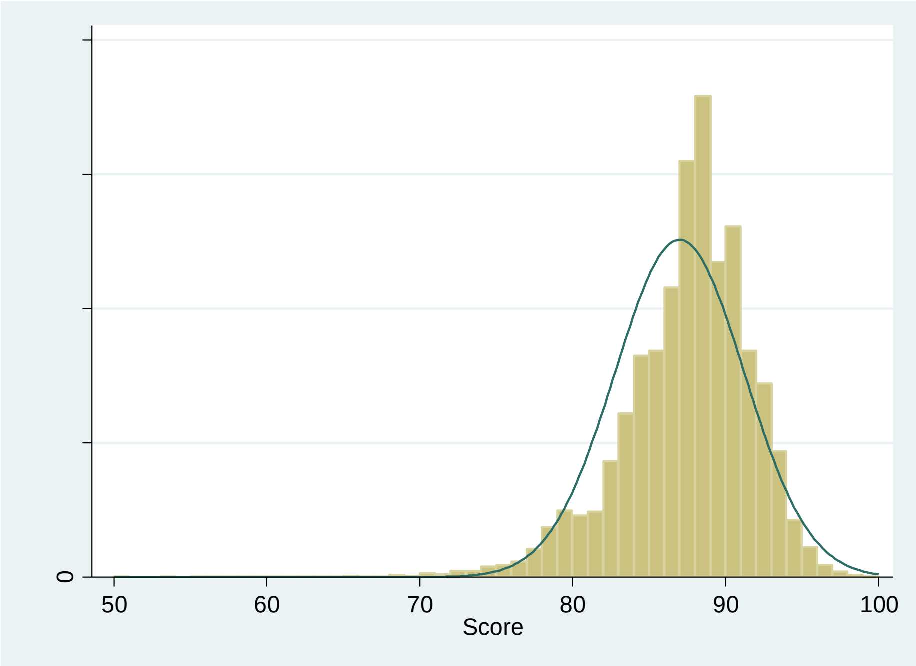


Figure A2: Distribution of log of real price