


ARTICLE

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

Stefano Castriota¹, Stefano Corsi² , Paolo Frumento¹ and Giordano Ruggeri²

¹Department of Political Sciences, University of Pisa, Pisa, Italy and ²Department of Agricultural and Environmental Science, Production, Territory, Agroenergies, University of Milan, Milan, Italy

Corresponding author: Stefano Corsi, email: stefano.corsi@unimi.it

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. The link between quality and price is positive, in line with the literature. 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 (on 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: price; quality; superstar; wine

JEL Classifications: L11; L66; Q11

1. Introduction

Over the last four decades, the wine sector has undergone major structural changes that have made it a highly globalized 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 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, and the link between price and quality has become particularly important.

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 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.

This research deepens and clarifies the relationship between the assessed quality and wine price by using a large database of 266,301 reviews published by Wine Spectator and exploring possible non-linearities. 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 receive well above 90 points, with the range of scores being 50–100. Only “superstar” wines benefit from 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 price dispersion is not constant across quality score values.

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 does the price premium attached to higher quality grow 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 investment levels (e.g., in agricultural and oenological equipment and treatments). The second has to do with the price at which 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 favorable scenario where the wine becomes a “superstar,” the dispersion of residuals becomes larger. The contribution of this research is twofold: it constructs and exploits a very large dataset on wine reviews and prices (to our knowledge, the largest ever analyzed); and it investigates potential non-linearities in the price-score connection.

The paper is organized as follows: the next section presents the relevant literature dealing with the topic. Then, Section III introduces the database and the source, Wine Spectator. Section IV presents the results of the empirical analysis divided into subsections for the different regression models. Finally, conclusions are presented in Section V.

II. Literature review

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, Tapia, and Warzynski, 2009; Masset, Weisskopf, and Cossutta, 2015). However, other research argues 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, Corsinovi, and Gaeta, 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, Faye, and Le Fur, 2020; Cacchiarelli et al., 2014; Caracciolo et al., 2016; Caracciolo and Furno, 2020; Costanigro, McCluskey, and Mittelhammer, 2007). In this regard, Costanigro, McCluskey, and Mittelhammer (2007) segment 13,024 Wine Spectator (WS) 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, Faye, and Le Fur (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 prices can be better explained by estimating quantile regressions across price categories, they find that the Robert Parker score 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 prices exhibit significant variability even among very similar products (Coppola, Sodano, and 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.

Rosen's superstar model (Rosen, 1981) argues that specific features and conditions can amplify inequality at the top of the wage distribution and generate extraordinarily high-paid "superstar" earners (Perri, 2014). While Rosen focuses on the television sector, where information technology allows a small number of talented individuals to serve a large market and reap significant rewards, other worker groups have been investigated, including doctors and lawyers (Rosen, 1983), dentists (Frank and Cook, 1995), CEOs (e.g., Gabaix and Landier, 2008), and agricultural workers (Hill and Burkhardt, 2021). More recently, the superstar theory has been applied to different sectors, such as music (e.g., Brooks, 2021), sports (e.g., Ferguson and Pinnuck, 2022), social media influencers (Lee and Theokary, 2021), academics (Hernández-Julián and Peters, 2022), and cities (Li et al., 2021).

According to Rosen (1981), the most valuable individuals, firms, and products gain much higher salaries, revenues, market share, and prices due to the size of the markets. The wine market has its unique characteristics, but the growing diffusion of international wine guides (e.g., Winespectator) widens the audience and enhances the visibility of wines with a better reputation and higher scores. To the best of our

knowledge, only one paper by Gibbs, Tapia, and Warzynski (2009) attempted to analyze the wine market from the superstar point of view.

III. Database

The source of the data analyzed in this paper is 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 *et al.*, 2018). Relying on a team of more than 15 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, 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 on 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's 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

In 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, and the United States. For the sake of consistency, we limited the analysis to 750 mL bottles and excluded bigger and smaller formats.

IV. Empirical analysis

A. 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 dollars, 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 WS is an American guide, it is understandable that 31.8% of the bottles rated are from the United

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

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. The average real prices look flat and grow exponentially once the score exceeds 90 points. Regressing the 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. A few bottles get less than 70 and more than 98 points.

B. 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 dependent variables (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

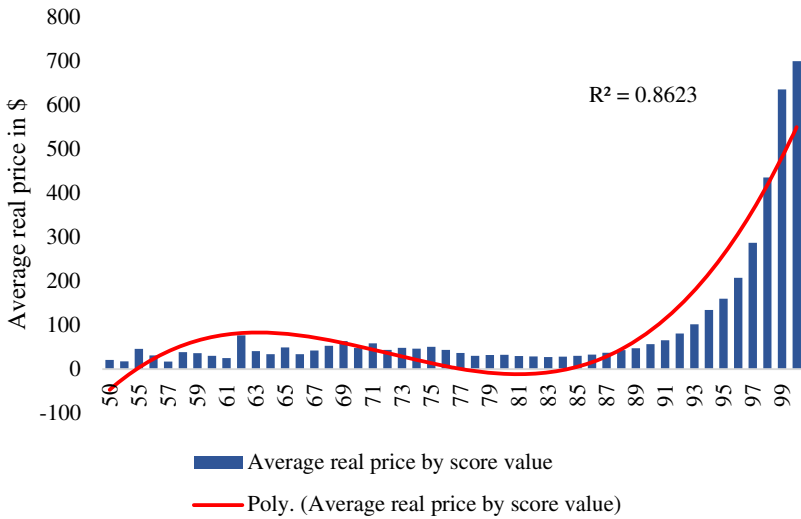


Figure 1. Average real price in \$ and quality score.

a simple cubic function.¹ The coefficients of the DVs of Column (5) are not shown for reasons of space but are available upon request; Figure 2 plots the values 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 at the upper end of the distribution. On average, the prices of wines with scores of between 50 and 90 points are statistically not different.

In Table A2 in the Appendix, we repeat regression 4 of Table 2 for each country, and the cubic effect of the score on the ln of price is confirmed for most countries.

C. Heteroskedastic hedonic regressions

In order to describe potential non-linear 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 splines² with two internal knots at score = (85, 90), year = (2000, 2011), and age = (5, 10). With the described definition, the design matrix $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n)\mathbf{T}$ is composed of 26 columns: the constant term,

¹Given the large number of observations, the R^2 and the adjusted R^2 are identical.

²Splines are a convenient way of modeling non-linear effects. While a quadratic term might be sufficient, it would also be less flexible than a spline function. Assuming a parabolic association is common in the econometric literature, but is a naïf approach with no theoretical justification. In contrast, using splines allows one to define a “flexible parametric model” in which additional degrees of freedom can easily be obtained by increasing the number of knots.

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

Variables	(1)	(2)	(3)	(4)	(5)
Age	0.120*** (0.0109)	0.0736*** (0.0157)	0.0602** (0.0195)	0.0591** (0.0198)	0.0587** (0.0201)
Dessert	0.370 (0.236)	0.277 (0.157)	0.250 (0.146)	0.241 (0.143)	0.248 (0.145)
Red	0.140 (0.145)	0.109 (0.130)	0.116 (0.120)	0.118 (0.118)	0.116 (0.117)
Rosé	-0.367*** (0.115)	-0.228*** (0.0686)	-0.214*** (0.0670)	-0.220*** (0.0703)	-0.214** (0.0713)
Sparkling	-0.0669 (0.123)	0.0238 (0.0688)	0.0467 (0.0595)	0.0503 (0.0575)	0.0503 (0.0548)
Drink now	-0.173 (0.102)	-0.241** (0.0990)	-0.154* (0.0825)	-0.136 (0.0761)	-0.135 (0.0819)
Score		0.0811*** (0.00577)	-0.762*** (0.108)	1.637*** (0.478)	
Score2			0.00496*** (0.000649)	-0.0246*** (0.00637)	
Score3				0.000120*** (2.83e-05)	
Constant	-13.97*** (1.874)	-13.61*** (2.552)	23.91*** (7.499)	-40.51*** (10.59)	-5.194 (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).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

four indicators of dessert, red, rosé, and sparkling wine (reference = White), the “drinknow” indicator, 11 country dummy variables (reference = Argentina), and the three-dimensional splines associated with the score, vintage year, and age. The mean regression model, that is, 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: a Normal heteroskedastic model and a quantile regression approach.

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

$$\mu(\mathbf{x}|\boldsymbol{\beta}) = \mathbf{x}^T \boldsymbol{\beta}, \log\{\sigma^2(\mathbf{x}|\boldsymbol{\theta})\} = \mathbf{x}^T \boldsymbol{\theta}. \quad (1)$$

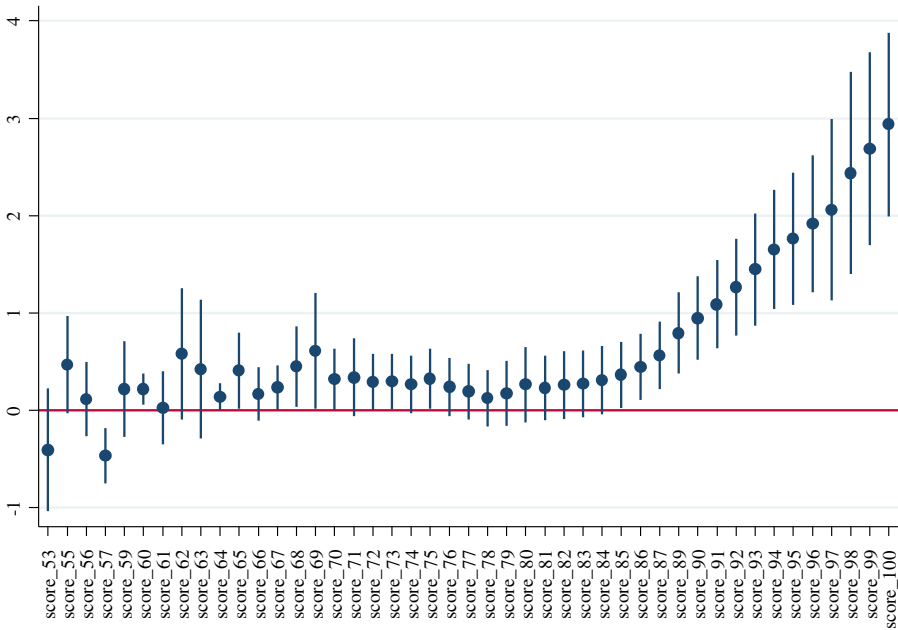


Figure 2. Coefficients and 95% confidence interval of the score DVs.
 Note: Results come from regression 5 in Table 2.

This modeling approach allows for accounting for the presence of heteroskedasticity directly. 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 $Q(p|\mathbf{x}, \boldsymbol{\beta}, \boldsymbol{\theta}) = \mu(\mathbf{x}|\boldsymbol{\beta}) + \sigma(\mathbf{x}|\boldsymbol{\theta})z(p)$, where $z(\cdot)$ is the quantile function of a $N(0,1)$ distribution. With our specification of the design matrix, the model had $26 + 26 = 52$ parameters, estimated by maximum likelihood. Standard errors were computed by applying standard asymptotic theory, that is, 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 3a show the predicted mean and median, the quartiles, and the 5th and 95th percentiles of $\ln(\text{price})$ 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, dispersion parameters also show a U-shaped association with the score. In Figure 4, we report the difference between the estimated 95th and 5th percentiles, which achieves a global minimum of approximately 87.5 points.

In our analysis, we assumed that different types of wines (white, red, rosé, sparkling, and dessert) have the same price-score relationship, up to an additive constant. This assumption may not be plausible and is rejected by the data, where we found a significant interaction ($p < 0.0001$) between the type of wine and the spline function that describes the price-score association. However, the effect of the score on price is qualitatively the same in all types of wines. The plot in Figure 3b is obtained by applying the Normal heteroskedastic model to each type of wine separately. It can be seen

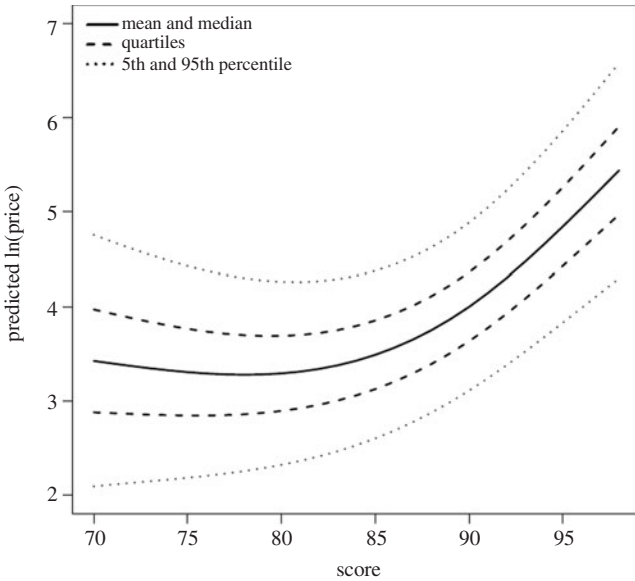


Figure 3a. Normal heteroskedastic model.

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

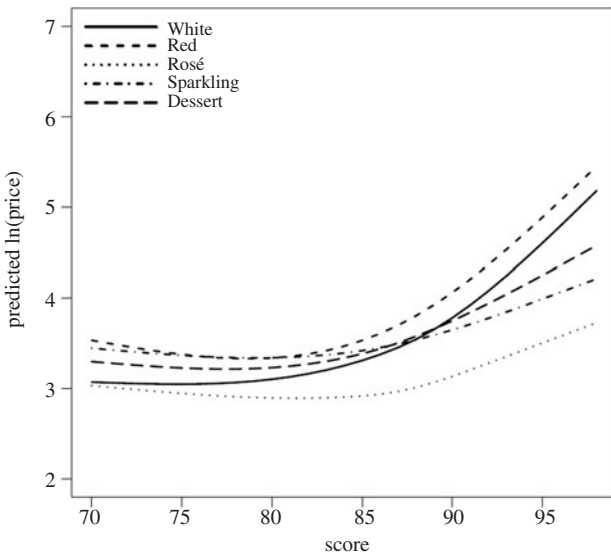


Figure 3b. Normal heteroskedastic model, by type of wine.

Note: Predicted mean of $\ln(\text{price})$, as a function of the quality score, as estimated by applying a Normal heteroskedastic model to each type of wine separately.

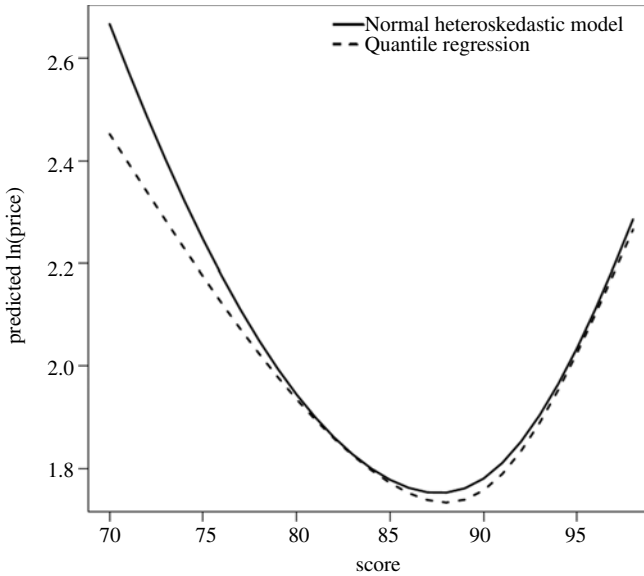


Figure 4. Difference between $Q(0.95)$ and $Q(0.05)$.

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

that the functions differ by more than just an additive constant; however, they all show a similar behavior: approximately flat for scores below 80, with a sharper increase for scores between 85 and 90. While this “justifies” our simplifying assumption to pool all wines together, we also understand that a stratified analysis could provide additional useful information; for example, red and white wines show a sharper increase in price than the other three groups.

Next, in Table A3, we applied the Normal heteroskedastic model using dummy variables for the score in place of spline functions. We report the estimated effects on the conditional mean (β) and log-standard deviation (θ). All the coefficients are highly significant. Results are consistent with those from the spline-based model: the minimum price is found in scores of 75–79, and a sharp increase is found for scores above 90. Moreover, the highest variance around the mean is found at very low and very high scores.

D. 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

$$Q(p|\mathbf{x}, \boldsymbol{\beta}) = \mathbf{x}^T \boldsymbol{\beta}(p). \quad (2)$$

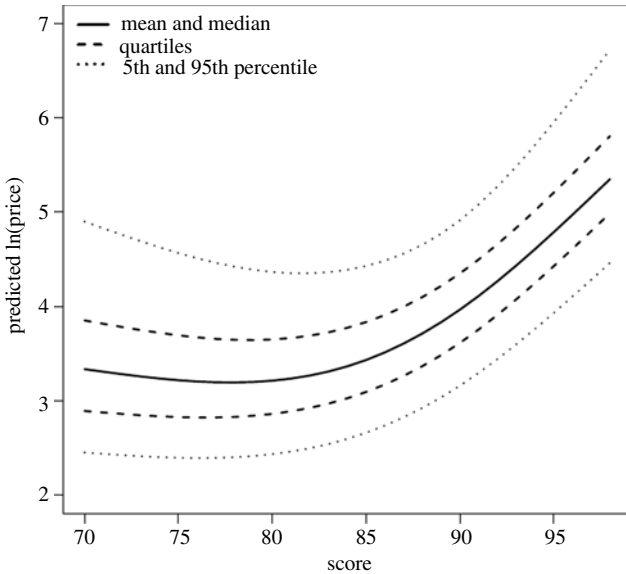


Figure 5. Quantile regression model.

Note: Predicted median, quartiles, and 5th and 95th percentiles of $\ln(\text{price})$, as a function of the quality score, as estimated by applying a Quantile regression model.

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

Estimation is carried out by minimizing a loss function

$$L(\beta) = \sum_i (p - u_i)(y_i - \mathbf{x}_i^T \beta(p)), \tag{3}$$

where $u = I(y \leq \mathbf{x}^T \beta(p))$ (e.g., Koenker, 2005), while standard errors can be computed by using non-parametric 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-quality score values. 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.

V. Conclusions

Quality is commonly considered the most important driver of wine prices. An extensive literature has shown a positive link between the two variables. This work provides new evidence using an extensive database of 266,301 bottles from 12 countries sold in the United States and rated by WS. 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 in the market and a premium on the retail price, the significant effect of wine quality on prices can only be achieved with outstanding scores. Hence, it seems reasonable to wonder whether the potential benefits in terms of price are worth the efforts and 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, that is, with a quality score higher than 90, beyond which prices increase considerably.

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

Even though our research is targeted at hedonic modelers, we believe it is important to mention the concerns about the potential benefits in terms of price from pursuing qualitative excellence. In order to provide definite policy suggestions, however, we should have information on a number of additional domains, such as firm investments and cost functions. With this respect, we acknowledge the limits of our work. Nevertheless, since the link between the quality of wines produced and firm profitability is crucial for wineries but unexplored by researchers, future investigations should focus on this topic.

Acknowledgments. The authors wish to thank (without implicating) Angelo Zago for the helpful comments in the early stages of this research and the reviewers and editors for their comments and constructive remarks.

References

- Ali, H. H., Lecocq, S., and Visser, M. (2018). The impact of gurus: Parker grades and en primeur wine prices. *World Scientific Handbook in Financial Economics Series*, 6, 437–457, https://doi.org/10.1142/9789813232747_0020.
- Ali, H. H., and Nauges, C. (2007). The pricing of experience goods: The Example of en primeur wine. *American Journal of Agricultural Economics*, 89(1), 91–103, <http://www.jstor.org/stable/4123565>.
- Amédée-Manesme, C. O., Faye, B., and Le Fur, E. (2020). Heterogeneity and fine wine prices: Application of the quantile regression approach. *Applied Economics*, 52(26), 2821–2840, <https://doi.org/10.1080/00036846.2019.1696937>.
- Ashton, R. H. (2014). Wine as an experience good: Price versus enjoyment in blind tastings of expensive and inexpensive wines. *Journal of Wine Economics*, 9(2), 171–182, <https://doi.org/10.1017/jwe.2014.7>.
- Ashton, R. H. (2016). The value of expert opinion in the pricing of Bordeaux wine futures. *Journal of Wine Economics*, 11(2), 261–288, <https://doi.org/10.1017/jwe.2016.6>.
- Bartlett, C. A. (2009). Global wine war 2009: New world versus old. Harvard Business School, Case Study No. 303–056, August. Purchase from <https://www.hbs.edu/faculty/Pages/item.aspx?num=37754>.
- Brooks R. (2021) Superstars and “the voice.” *Applied Economics Letters*, 28(20), 1797–1800, <https://doi.org/10.1080/13504851.2020.1854435>.

- Cacchiarelli, L., Carbone, A., Laureti, T., and Sorrentino, A. (2014). The value of quality clues in the wine market: Evidences from Lazio, Italy. *Journal of Wine Research*, 25(4), 281–297, <https://doi.org/10.1080/09571264.2014.959659>.
- Caracciolo, F., D'Amico, M., Di Vita, G., Pomarici, E., Bianco, A. D., and Cembalo, L. (2016). Private vs. collective wine reputation. *International Food and Agribusiness Management Review*, 19(3), 191–210, <https://doi.org/10.22004/ag.econ.244704>.
- Caracciolo, F., and Furno, M. (2020). Hedonic functions, heterogeneous consumers, and wine market segmentation. *Journal of Agricultural and Resource Economics*, 45(2), 299–316, <https://doi.org/10.22004/ag.econ.302456>.
- Cardebat, J. M. (2017). *Economie du Vin*. Paris: La Decouverte.
- Cardebat, J. M., Corsinovi, P., and Gaeta, D. (2018). Do top 100 wine lists provide consumers with better information? *Economics Bulletin*, 38(2), 983–994.
- Cardebat, J. M., Faye, B., Le Fur, E., and Storchmann, K. (2017). The law of one price? Price dispersion on the auction market for fine wine. *Journal of Wine Economics*, 12(3), 302–331, <https://doi.org/10.1017/jwe.2017.32>.
- Castriota, S. (2020). *Wine Economics*. Boston, MA: The MIT Press.
- Chen, B., Velchev, V., Palmer, J., and Atkison, T. (2018). Wineinformatics: A quantitative analysis of wine reviewers. *Fermentation*, 4(4), 1–16, <https://doi.org/10.3390/fermentation4040082>.
- Chossat, V., and Gergaud, O. (2003). Expert opinion and gastronomy: The recipe for success. *Journal of Cultural Economics*, 27(2), 127–141.
- Coppola, A., Sodano, V., and Verneau, F. (2001). Explaining price dispersion in the Campania market for wine. Vineyard Data Quantification Society Working Papers, Naples, Italy. <http://wpage.unina.it/vsodano/explaining-price.pdf>.
- Costanigro, M., McCluskey, J. J., and Mittelhammer, R. C. (2007). Segmenting the wine market based on price: Hedonic regression when different prices mean different products. *Journal of Agricultural Economics*, 58(3), 454–466, <https://doi.org/10.1111/j.1477-9552.2007.00118.x>.
- Dubois, P., and Nauges, C. (2010). Identifying the effect of unobserved quality and expert reviews in the pricing of experience goods: Empirical application on Bordeaux wine. *International Journal of Industrial Organization*, 28(3), 205–212, <https://doi.org/10.1016/j.ijindorg.2009.08.003>.
- Ferguson, P. J., and Pinnuck, M. (2022). Superstar productivity and pay: Evidence from the Australian football league. *Economic Record*, in press, <https://doi.org/10.1111/1475-4932.12665>.
- Ferro, G., and Benito Amaro, I. (2018). What factors explain the price of top quality wines? *International Journal of Wine Business Research*, 30(1), 117–134, <https://doi.org/10.1108/IJWBR-05-2017-0036>.
- Frank, R. H., and Cook, P. J. (1995). *The Winner-Take-All Society*. New York: Free Press.
- Gabaix, X., and Landier, A. (2008) Why has CEO pay increased so much? *Quarterly Journal of Economics*, 123(1), 49–100, <https://www.jstor.org/stable/25098894>.
- Gibbs, M., Tapia, M., and Warzynski, F. (2009). Globalisation, superstars, and reputation: Theory and evidence from the wine industry. *Journal of Wine Economics*, 4(1), 46–61, <https://doi.org/10.1017/s1931436100000675>.
- Goldstein, R., Almenberg, J., Dreber, A., Emerson, J. W., Herschkowitsch, A., and Katz, J. (2018). Do more expensive wines taste better? Evidence from a large sample of blind tastings. *World Scientific Handbook in Financial Economics Series*, 6(1), 535–545, https://doi.org/10.1142/9789813232747_0025.
- Gottschalk, F. (2018). What characterises credence goods? A critical look at the literature. *SSRN Electronic Journal*, (January 2018). Available at <https://doi.org/10.2139/ssrn.3114257>.
- Hay, C. (2010). The political economy of price and status formation in the Bordeaux en primeur market: The role of wine critics as rating agencies. *Socio-Economic Review*, 8(4), 685–707, <https://doi.org/10.1093/ser/mwq007>.
- Hernández-Julían, R., and Peters, C. (2022). Why try? The superstar effect in academic performance. *Eastern Economic Journal*, 48, 147–165, <https://doi.org/10.1057/s41302-021-00197-5>.
- Hill, A. E., and Burkhardt, J. (2021). Peers in the field: The role of ability and gender in peer effects among agricultural workers. *American Journal of Agricultural Economics*, 103(3), 790–811, <https://doi.org/10.1111/ajae.12192>.
- Jaeger, D. A., and Storchmann, K. (2011). Wine retail price dispersion in the United States: Searching for expensive wines? *American Economic Review*, 101(3), 136–141, <https://doi.org/10.1257/aer.101.3.136>.
- Koenker, R. (2005). *Quantile Regression (Econometric Society Monographs)*. New York: Cambridge University Press.

- Lee, M. T., and Theokary, C. (2021). The superstar social media influencer: Exploiting linguistic style and emotional contagion over content? *Journal of Business Research*, 132, 860–871, <https://doi.org/10.1016/j.jbusres.2020.11.014>.
- Li, B., Jin, C., Jansen, S. J. T., van der Heijden, H., and Boelhauer, P. (2021). Residential satisfaction of private tenants in China's superstar cities: The case of Shenzhen, China. *Cities*, 118, 103355, <https://doi.org/10.1016/j.cities.2021.103355>.
- Masset, P., Weisskopf, J.-P., and Cossutta, M. (2015). Wine tasters, ratings, and en primeur prices. *Journal of Wine Economics*, 10(1), 75–107, <https://doi.org/10.1017/jwe.2015.1>.
- Perri, T. (2014). Substitution and superstars. *Economics Letters*, 125(2), 240–242, <https://doi.org/10.1016/j.econlet.2014.08.032>.
- Rebelo, J., Lourenço-Gomes, L., Gonçalves, T., and Caldas, J. (2019). A hedonic price analysis for the Portuguese wine market: Does the distribution channel matter? *Journal of Applied Economics*, 22(1), 40–59, <https://doi.org/10.1080/15140326.2018.1550596>.
- Rosen, S. (1981). The economics of superstars. *American Economic Review*, 71(5), 845–858, <http://www.jstor.org/stable/1803469>.
- Rosen, S. (1983). Specialisation and human capital. *Journal of Labor Economics*, 1(1), 43–49, <http://www.jstor.org/stable/2534930>.
- Schnabel, H., and Storchmann, K. (2010). Prices as quality signals: Evidence from the wine market. *Journal of Agricultural and Food Industrial Organization*, 8(1), 1–21, <https://doi.org/10.2202/1542-0485.1283>.
- Thornton, J. (2013). *American Wine Economics: An Exploration of the U.S. Wine Industry*. Berkeley: University of California Press.

Appendix

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 A2. First stage, determinants of ln of real wine price, by country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Variables	Italy	France	Germany	Spain	Portugal	Argentina	Australia	Canada	Chile	New Zealand	South Africa	USA	Italy	France
Age	0.0113*** (0.00187)	0.0262*** (0.00246)	0.0889*** (0.0173)	0.0865*** (0.00285)	0.0233*** (0.00401)	0.195*** (0.00554)	0.129*** (0.00609)	0.222*** (0.0269)	0.169*** (0.00676)	0.189*** (0.00705)	0.126*** (0.00508)	0.109*** (0.00186)	0.0156*** (0.00196)	0.0253*** (0.00224)
Dessert	-0.00372 (0.0213)	0.0450 (0.0690)	1.402*** (0.0525)	0.303** (0.122)	0.375*** (0.0312)	-0.0211 (0.113)	0.144 (0.140)	0.290* (0.160)	-0.0714 (0.277)	-0.0635 (0.0680)	-0.0464 (0.0570)	0.0222 (0.0596)	-0.115*** (0.0216)	0.454*** (0.0659)
Red	0.0689*** (0.00887)	-0.180*** (0.00538)	0.540*** (0.0607)	0.0332*** (0.0105)	0.151*** (0.0175)	-0.0408*** (0.0115)	0.137*** (0.0106)	0.195*** (0.0507)	-0.00177 (0.0102)	0.245*** (0.0120)	0.0534*** (0.0114)	0.302*** (0.00385)	-0.0439*** (0.00965)	0.0595*** (0.00602)
Rosé	-0.0241 (0.0455)	-0.582*** (0.0398)		-0.231*** (0.0158)	-0.0580 (0.0413)	0.0743** (0.0297)	0.0357 (0.0389)		0.0722*** (0.0256)	-0.0698 (0.0506)	0.0173 (0.0244)	-0.148*** (0.0102)	-0.00655 (0.0425)	-0.0329 (0.0330)
Sparkling	-0.126*** (0.0268)	0.234** (0.104)	0.230** (0.107)	0.0970*** (0.0228)	0.185*** (0.0646)	0.194*** (0.0693)	0.0762 (0.0581)		0.521*** (0.0955)	-0.0955** (0.0477)	0.0792 (0.0544)	0.0830*** (0.0137)	-0.0500* (0.0299)	0.0617 (0.0791)
Drink now	0.0659*** (0.00588)	-0.290*** (0.00515)	-0.0931*** (0.0117)	-0.193*** (0.0159)	-0.258*** (0.0244)	0.0203 (0.0258)	-0.208*** (0.0116)	-0.0705 (0.0855)	-0.0388* (0.0216)	-0.150*** (0.0236)	-0.0699*** (0.0250)	-0.175*** (0.00471)	0.0631*** (0.00631)	-0.0773*** (0.00480)
Score	0.320 (0.641)	2.039*** (0.111)	0.809*** (0.203)	2.184*** (0.232)	-1.001 (0.646)	4.332*** (0.345)	1.734** (0.881)	8.124 (5.042)	2.044*** (0.392)	5.642*** (0.776)	2.790*** (0.246)	0.281** (0.116)	0.248 (0.626)	2.488*** (0.0982)
Score2	-0.0107 (0.00759)	-0.0298*** (0.00136)	-0.0128*** (0.00256)	-0.0311*** (0.00295)	0.00870 (0.00770)	-0.0598*** (0.00433)	-0.0286*** (0.0104)	-0.102* (0.0601)	-0.0307*** (0.00488)	-0.0714*** (0.00924)	-0.0397*** (0.00317)	-0.00579*** (0.00141)	-0.00955 (0.00741)	-0.0350*** (0.00121)
Score3	7.20e-05*** (2.99e-05)	0.000143*** (5.57e-06)	6.60e-05*** (1.07e-05)	0.000148*** (1.24e-05)	-1.77e-05 (3.06e-05)	0.000272*** (1.81e-05)	0.000147*** (4.05e-05)	0.000423* (0.000239)	0.000150*** (2.02e-05)	0.000300*** (3.66e-05)	0.000186*** (1.35e-05)	3.54e-05*** (5.66e-06)	6.61e-05** (2.92e-05)	0.000163*** (4.98e-06)

(Continued)

Table A2. (Continued.)

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	(13) Italy	(14) France
Collective reputation													0.0239*** (0.00245)	0.107*** (0.00242)
Constant	8.154 (17.97)	-45.74*** (3.004)	-14.08*** (5.337)	-50.69*** (6.078)	33.87* (18.04)	-101.3*** (9.091)	-28.31 (24.97)	-214.1 (140.8)	-41.69*** (10.49)	-145.4*** (21.71)	-62.00*** (6.346)	-0.824 (3.204)	9.205 (17.55)	-58.18*** (2.645)
Region DVs	No	No	No	No	No	No	No	No	No	No	No	No	Yes	Yes
Observations	46,148	64,414	10,101	15,882	5,356	6,924	13,522	345	7,125	5,589	6,348	84,547	46,148	64,414
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	0.359	0.638

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

Table A3. Normal heteroskedastic model using dummy variables for the score, in place of spline functions.

Category of scores	n	β	θ
50–74 (not recommended)	2,278	ref	ref
75–79 (mediocre)	12,874	-0.089	-0.123
80–84 (good)	46,819	0.063	-0.249
85–89 (very good)	12,8810	0.333	-0.245
90–94 (outstanding)	71,122	0.828	-0.195
95–100 (classic)	3,770	1.531	-0.042

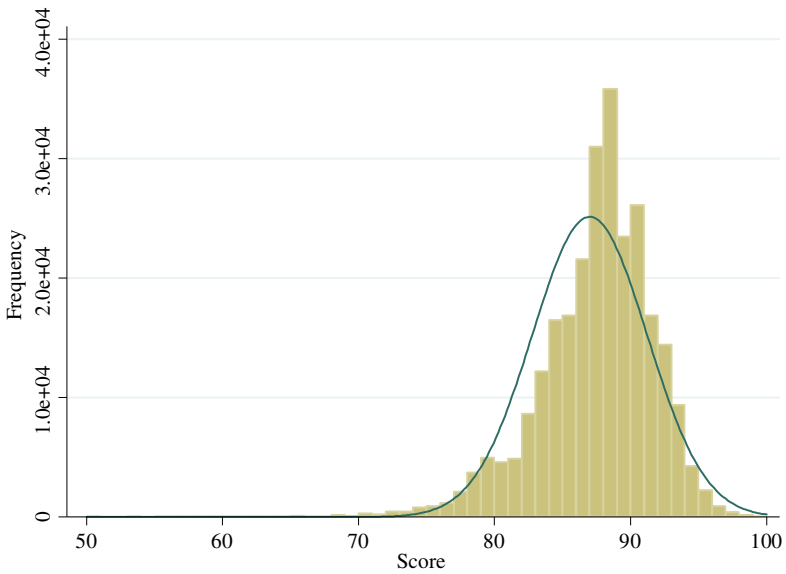


Figure A1. Distribution of score values.

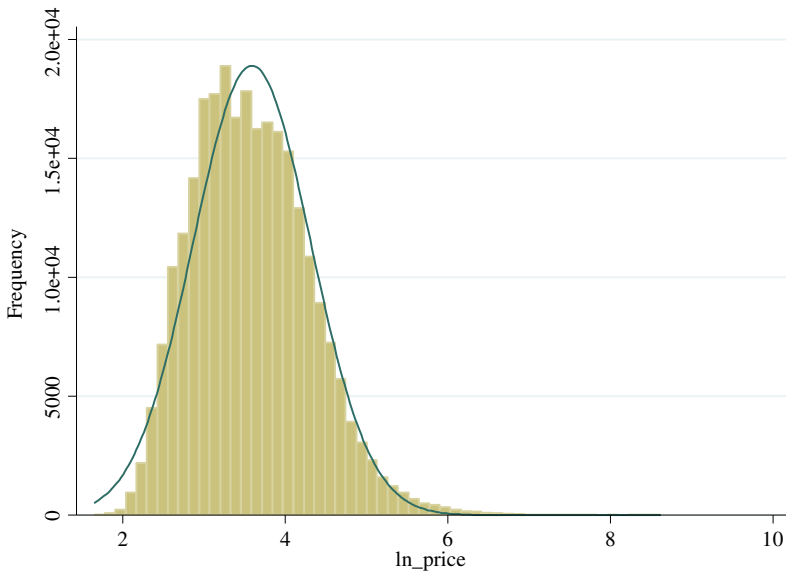


Figure A2. Distribution of log of real price.