MODELING WINE RANKINGS BASED ON WINE LABEL ATTRIBUTES: A CROSS-COUNTRY COMPARISON WITH NEW WORLD WINES

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ABSTRACT

This paper compares different predictive econometric models for cross-country studies on wines, utilizing different wine label attributes, using the rich database from the *Wine Spectator* website [2017]. We find that discrete choice models like ordered logit and probit models perform better than the linear regression models (OLS and truncated OLS), using an out-of-sample cross validation technique for comparison. Further, price is found to be a good indicator of quality in all our models. Another major finding is that the wines from the US ranks higher compared to those from other "New World" wines, while vintage does not have a significant effect on wine quality. Merlot wines score higher than Cabernet Sauvignon variety.

Keywords: Consumer's preference, discrete choice models, wine quality-rankings, wine label attributes.

INTRODUCTION

Quality of wines and their pricing has been a topic of interest ever since we have started to consume them. Since wine is an experience good[1], consumer choice is often influenced by quality evaluations by experts, available in rating by *Wine Spectator*, *Wine Advocate* and other such consumer reports by Roberts and Reagans [2007]. There have been previous attempts to study the relationship between price and quality in the wine industry, for example by Landon and Smith [1998] and Corduas [2013]. An extensive review on consumers' behaviour towards wine purchasing is available in Lockshin and Corsi [2012]. Most of the above-mentioned literature have focused on how wine pricing is determined by many attributable factors including wine quality, colour, types of wine, alcohol content, producer's name, bottle weight, vintage, region, etc. However, not much research has been done on how market-determined price (as an exogenous factor) might influence expected product quality in terms of a consumer's willingness to buy a higher quality wine in association with other wine label attributes, which is the focus of our paper. Likewise, most of the literature that studies price-quality relationships, are based on data from the European (Old World) wine industries. However, there are only a few such cross-country studies on the wines from the New World, e.g., the US, Australia and Canada. Our paper is an attempt to fill this gap in the literature.

OBJECTIVE AND RESEARCH QUESTIONS

The objective of this paper is to utilize the rich Wine Spectator (WS) database of *two* red wine varietals (*Cabernet Sauvignon* and *Merlot*) including experts' rankings across four wine producing countries (*USA*, *Chile*, *Canada* and *Australia*). Utility from a good quality wine is assumed to be represented by score obtained from the Wine Spectator ranking, blindly assigned by the famous wine experts. It is assumed that

[1] An experience good is one whose quality is difficult to observe before consuming (experiencing) it (Nelson (1970)).

the experts' rankings are driven by the varying strength of consumers' preferences towards good quality wines. The underlying utility depends on various intrinsic and extrinsic wine characteristics, appearing in the wine product labels. We try to investigate the effects of *four* wine label characteristics: market-derived *price*, *varietal type* (Cabernet Sauvignon versus Merlot), *country* (USA vs. Chile, Canada, Australia); and *vintage-year* on *rankings*. In particular, we would like to address the following questions:

- What is the effect of market-derived price towards wine quality? Is the relationship positive consistent with previous studies based on Old World wine industries?
- Is there a ranking variation among wines produced in USA compared to the other three major "New World" wine producing countries, namely Australia, Canada and Chile?
- Which of the following type of Econometric models – discrete choice models (ordered probit and logit models) or ordinary least squares models – are superior in terms of predictive ability?
- There is often a general perception among wine lovers that aged wines taste better. Is this perception indeed true in the sense that vintage wines get a higher quality ranking, under blind tasting by experts?

DATA

Data used on this paper is based on the unique Wine Spectator database consisting of more than 11,000 wine samples. Wine rankings data for the varietal-type `Cabernet Sauvignon' and `Merlot' has been *manually* extracted from the Wine Spectator website [2017] (http://www.winespectator.com) including winery, country, vintage, market-determined price and individual score. A selected set of attributes from this database that we are using in our current analysis, are listed below:

- *Wine Spectator rankings* – raw scores are blindly assigned by wine experts on a 0 – 100 scales. Fairly good quality wines are selected with score ranges between 80 and 100 (21 distinct individual scores). Individual scores are further classified as '*Good*' (if raw score ≤ 84), '*Very Good*' (if 85 ≤ raw score ≤ 89), '*Outstanding*' (if 90 ≤ raw score ≤ 94), and '*Classic*' (if raw score ≥ 95) according to the "Wine Spectator" scoring system.
- *Market derived price* (per 750 ml) with a cut-off maximum value of $150.
- *Two wine types* – Cabernet Sauvignon (7571) and Merlot (4197).
- *Four countries* – USA (7569), Chile (1564), Canada (67), and Australia (2558)
- *Vintage* – Production year ranges from 1974 to 2016.

Table 1a Descriptive statistics for ranking categories and their distribution (frequencies)

Variable	**Total N=11768**	**80 ≤ Score ≤ 84 N=2555**	**85 ≤ Score ≤ 89 N=5853**	**90 ≤ Score ≤ 94 N=3122**	**95 ≤ Score ≤ 100 N=238**	p-value
Log(price)						
Mean (SD)	3.317 (0.753)	2.744 (0.604)	3.236 (0.649)	3.856 (0.601)	4.418 (0.591)	0.000
Range	1.386 – 5.011	1.386 – 5.010	1.386 – 5.011	1.946 – 5.011	2.485 – 5.011)	(SLR)
Country						
USA	7579	1322	3566	2466	225	0.000
Chile	1564	659	717	178	10	(Chi-
Canada	67	19	37	11	0	SQ)
Australia	2558	555	1533	467	3	
Varietal						0.000
Cabernet Sauvignon	7571	1370	3763	2205	233	(Chi-SQ)
Merlot	4197	1185	2090	917	5	

EMPIRICAL METHODOLOGIES

Utilizing the rich database of Wine Spectator rankings, the effects of wine label attributes are investigated through OLS (ordinary least square) and truncated OLS models [Takeshi, 1973]. Individual raw scores between 80 and 100 are modelled through the following linear regression models:

$$Rank_i = \beta_0 + \beta_1 \log(Price)_i + \beta_2 Merlot_i + \beta_3 Australia_i + \beta_4 Canada_i + \beta_5 Chile_i + \beta_6 Vintage_i + \varepsilon_i, \quad where\ 80 \le Rank_i \le 100 \qquad (1)$$

$$\varepsilon_i \sim N(0, \sigma_i^2) \text{ for OLS regression model}$$

$$\varepsilon_i \sim truncated - N(0, \sigma_i^2)\ for\ double\ truncated\ regression\ model$$

Here the effect of the wine variety $Merlot$ is compared against its competitive variety $Cabernet\ Sauvignon$. Regional effects of the countries $Australia$, $Canada$, $Chile$ are compared against USA. Market derived price per 750 ml (as an exogenous factor) is denoted as $Price_i$ and $Vintage_i$ is the year of production. Data on all these variables are listed in the *Wine Spectator* database.

So far, most wine industry researchers have considered the *ordered probit model* as their preferred mode of regression estimation while investigating the effect of price or other attributable characteristics on wine quality rankings [e.g., Lockshin and Rhodus, 1993; Goldstein et al., 2008]. Greene and Hensher [2008, Chapter 5] describes the details of the discrete choice models for ordered responses. The observed responses of four quality ranking categories can be modeled through a latent variable y_i^* through the following random utility regression model:

$$y_i^* = \beta_1 \log(Price)_i + \beta_2 Merlot_i + \beta_3 Australia_i + \beta_4 Canada_i + \beta_5 Chile_i + \beta_6 Vintage_i + \varepsilon_i, \qquad (2)$$

$$Rank_i \begin{cases} = Good\ (1) & if\ y_i^* < \mu_1 \\ = Very\ Good\ (2) & if\ \mu_1 \le y_i^* < \mu_2 \\ = Outstanding\ (3) & if\ \mu_2 \le y_i^* < \mu_3 \\ = Classic\ (4) & if\ \mu_3 \le y_i^* \end{cases}$$

$$where\ f(\varepsilon_i) = \frac{\exp(-(\varepsilon_i/\sigma_i)^2/2)}{\sqrt{2\pi}\sigma}\ for\ probit\ model \qquad (2a)$$

$$and\ \ f(\varepsilon_i) = \frac{\exp(\varepsilon_i/\sigma_i)}{[1+\exp(\varepsilon_i/\sigma_i)]^2}\ for\ logit\ model \qquad (2b)$$

Accordingly, the random error term ε_i follows a conventional cumulative distribution function (cdf), denoted as $F(\varepsilon_i|\boldsymbol{x_i}) = F(\varepsilon_i)$. Possible heteroscedasticity in the proposed ordered probit and logit models is addressed through the robust "sandwich" estimator for the asymptotic covariance matrix proposed by White [1980], as inherently calculated by STATA. The latent variable equation (2) can be rewritten in the following general format with $\boldsymbol{x_i}$ being a vector of six covariates and $\boldsymbol{\beta}$ being the associated coefficient vector, to be estimated along with the range parameters μ_1, μ_2 and μ_3.

$$y_i^* = \boldsymbol{\beta}'\boldsymbol{x_i} + \varepsilon_i \qquad (3)$$

The likelihood probabilities for the ordered ranks are

$$Prob[Rank_i = 1\ |x_i] = Prob[y_i^* < \mu_1] = Prob[\varepsilon_i < \mu_1 - \boldsymbol{\beta}'\boldsymbol{x_i}) = \mathrm{F}(\mu_1 - \boldsymbol{\beta}'\boldsymbol{x_i})$$
$$Prob[Rank_i = 2\ |x_i] = Prob[\mu_1 \le y_i^* < \mu_2\ ] = \mathrm{F}(\mu_2 - \boldsymbol{\beta}'\boldsymbol{x_i}) - \mathrm{F}(\mu_1 - \boldsymbol{\beta}'\boldsymbol{x_i})$$
$$Prob[Rank_i = 3\ |x_i] = Prob[\mu_2 \le y_i^* < \mu_3\ ] = \mathrm{F}(\mu_3 - \boldsymbol{\beta}'\boldsymbol{x_i}) - \mathrm{F}(\mu_2 - \boldsymbol{\beta}'\boldsymbol{x_i})$$
$$Prob[Rank_i = 4\ |x_i] = Prob[\mu_3 \le y_i^*\ ] = 1 - \mathrm{F}(\mu_3 - \boldsymbol{\beta}'\boldsymbol{x_i}) = F(\boldsymbol{\beta}'\boldsymbol{x_i} - \mu_3)$$

The marginal effects or the changes in the probabilities for the ordered probit and logit models are derived separately depending on $\boldsymbol{x}$ being continuous or discrete (dummy) variable in the following manner:

Case 1: x is continuous variable (e.g., $\log(Price_i)$)

$$\delta_1(\boldsymbol{x_i}) = \frac{\delta[Prob(Rank = 1 \mid \boldsymbol{x_i})]}{\delta[\boldsymbol{x_i}]} = [f(\mu_1 - \boldsymbol{\beta}'\boldsymbol{x_i})](-\beta) \quad (4)$$

$$\delta_2(\boldsymbol{x_i}) = \frac{\delta[Prob(Rank = 2 \mid \boldsymbol{x_i})]}{\delta[\boldsymbol{x_i}]} = [f(\mu_1 - \boldsymbol{\beta}'\boldsymbol{x_i}) - f(\mu_2 - \boldsymbol{\beta}'\boldsymbol{x_i})]\beta \quad (5)$$

$$\delta_3(\boldsymbol{x_i}) = \frac{\delta[Prob(Rank = 3 \mid \boldsymbol{x_i})]}{\delta[\boldsymbol{x_i}]} = [f(\mu_2 - \boldsymbol{\beta}'\boldsymbol{x_i}) - f(\mu_3 - \boldsymbol{\beta}'\boldsymbol{x_i})]\beta \quad (6)$$

$$\delta_4(\boldsymbol{x_i}) = \frac{\delta[Prob(Rank = 4 \mid \boldsymbol{x_i})]}{\delta[\boldsymbol{x_i}]} = [f(\boldsymbol{\beta}'\boldsymbol{x_i} - \mu_3)](\beta) \quad (7)$$

Where $f(.)$ denotes the respective probability density function (pdf) for Normal (probit) and Logistic distribution.

Case 2: x is discrete variable (e.g., $Merlot_i$) with 2 levels

$$ME\ (x =' \ Merlot\ ', w.r.t\ x =' \ Cabernet\ Sauvignon\ ')$$
$$= \left[Prob\left(Rank_i = j \middle| \bar{X}_{(d)}, x =' \ Merlot\ '\right)\right]$$
$$- \left[Prob\left(Rank_i = j \middle| \bar{X}_{(d)}, x =' \ Cabernet\ Sauvignon\ '\right)\right]; \quad (8)$$

Where $\bar{X}_{(d)}$, denotes the means of all other variables in the model and $j = '\ 1\ ','\ 2\ ','\ 3\ '\ \&\ '\ 4\ '$.

Models are compared based on out-of-sample k-fold cross validation technique, as in Kohavi [1995]. The entire wine dataset is randomly divided into K mutually exclusive subgroups of approximately equal size. Out-of-sample ranking predictions are made for the $k-th$ ($k = 1, \dots, K$) group utilizing model estimates from the rest of the samples in $K-1$ groups. Both root mean squared error (RMSE) and absolute error-difference (ABSE) are calculated comparing observed and predicted individual rankings (or four ranking categories for the discrete choice models) for the $k-th$ group, same repeated over all the K groups.

RESEARCH FINDINGS

The main findings from of the paper are summarized below.

- First, all models show that price has a significant positive effect on ranking for the wines, further supporting the price-quality hypothesis from related market research studies. (Table 2a – 2c)
- Merlot wines compared to Cabernet Sauvignon variety have a significant negative impact on the probability for higher quality wine rankings. (Table 2a – 2c)
- The wines from Australia, Canada and Chile with respect to the wines from USA have significant negative effects on the higher quality ranking. Cross country comparison implies USA produced wines receive higher rankings compared to Australia, Canada and Chile. (Figure 1 and Table 2a – 2c)
- Vintage does not have any significant effect on the likelihood of various wine quality rankings, which contradicts the conventional expectation. (Table 2a – 2c)
- Results from K-fold ($K = 100$) cross validation implies models with price provide slightly better prediction compared to model without price. This observation is expected as price is an influential factor in predicting good quality products [Rao and Monroe 1989; Plassmann et al. 2008]. (Table 3)
- Both RMSE and ABSE estimates are significantly smaller for the discrete choice models (ordered probit and logit) compared to linear models (OLS and truncated OLS). This is reasonable, since for the linear models, the variability across rankings are much larger (twenty-one distinct individual rankings) compared to discrete choice models (four ranking categories). (Table 3)
- Therefore, we propose the efficient model for predicting wine quality rankings as ordered probit model following the conventional modelling approach of many market researchers in the similar field.

Nonetheless, consumers are likely to prefer qualitative rankings (for example, '*Outstanding*' versus '*Good*') rather than individual rankings assigned by the wine experts.

Figure 1 Country-specific box plots of wine score

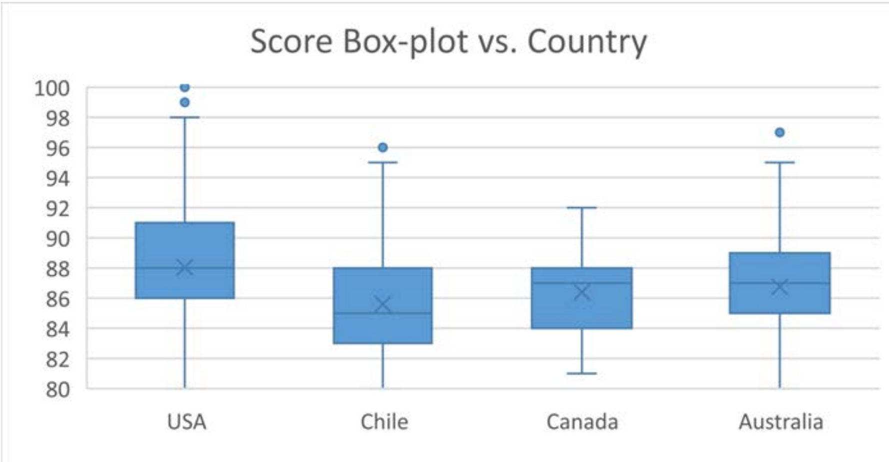

Table 2a Coefficient estimates (robust – SE) from OLS and truncated OLS regression models

Wine attributes	OLS		Truncated Regression
	With Price	Without Price	With Price
Log(price)	2.65*** (0.05)	--	2.67*** (0.05)
Merlot	-0.57 *** (0.06)	-1.68 *** (0.07)	-0.58 *** (0.06)
Australia	-0.27 *** (0.07)	-1.83 *** (0.07)	-0.34 *** (0.07)
Canada	-1.64 *** (0.28)	-1.63 *** (0.37)	-1.85 *** (0.31)
Chile	-0.29 *** (0.08)	-2.71 *** (0.09)	-0.45 *** (0.09)
Vintage	0.01 (0.01)	0.04 (0.03)	0.00 (0.01)
Constant	64.53 *** (13.16)	-1.72 (56.87)	69.83 *** (11.85)

Coefficient significance is reported as ***, ** and * for 1%, 5% and 10% level of significance respectively.

Table 2b Coefficient estimates (robust – SE) from ordered probit and ordered logit models

Wine attributes	Ordered probit		Ordered logit
	With Price	Without Price	With Price
Log(price)	0.947 *** (0.020)	--	1.646 *** (0.045)
Merlot	-0.193 *** (0.024)	-0.507 *** (0.024)	-0.318 *** (0.045)
Australia	-0.071 ** (0.028)	-0.536 *** (0.026)	-0.099 * (0.052)
Canada	-0.591 *** (0.129)	-0.499 *** (0.138)	-1.026 *** (0.223)

Chile	-0.169 *** (0.036)	-0.891 *** (0.036)	-0.280 *** (0.070)
Vintage	0.001 (0.002)	0.012 (0.008)	0.009 (0.007)

Table 2c Estimated partial effects (evaluated at conditional mean): $\frac{dy}{dx}$ from ordered probit regression

Wine attributes	**80 ≤ Score ≤ 84** (0.218)	**85 ≤ Score ≤ 89** (0.497)	**90 ≤ Score ≤ 94** (0.265)	**95 ≤ Score ≤ 100** (0.020)
Log(price)	-0.231 *** (0.005)	-0.062 *** (0.005)	0.280 *** (0.007)	0.013 *** (0.001)
Merlot	0.047 *** (0.006)	0.012 *** (0.002)	-0.057 *** (0.007)	-0.003 *** (0.000)
Australia	0.017 ** (0.007)	0.005 ** (0.002)	-0.021 ** (0.008)	-0.001 ** (0.000)
Canada	0.144 *** (0.031)	0.039 *** (0.009)	-0.174 *** (0.038)	-0.008 *** (0.002)
Chile	0.041 *** (0.009)	0.011 *** (0.002)	-0.050 *** (0.010)	-0.002 *** (0.000)
Vintage	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 0.000

Table 3 100-fold cross validation results

Model	**RMSE_price**	**RMSE_no-price**	**ABSE_price**	**ABSE_no-price**
OLS	2.792	3.304	2.232	2.612
Truncated OLS	2.790	--	2.230	--
Ordered probit	0.689	0.750	0.450	0.520
Ordered logit	0.689	0.740	0.449	0.504

Note. RMSE_price: Root mean square error from the model with price**;** RMSE_no-price: Root mean square error from the model without price; ABSE_price: Absolute error from the model with price**;** BSE_no-price: Absolute error from the model without price.

CONCLUDING REMARKS AND FUTURE RESEARCH

This paper has used data on more than 11,000 wine samples, *manually extracted* from the unique Wine Spectator database consisting of two red wine varietals (Cabernet Sauvignon and Merlot) across four wine producing countries (USA, Chile, Canada and Australia). Four predictive models (OLS, truncated OLS, ordered probit and ordered logit) are estimated to investigate the effects of the wine label characteristics (price, country of origin, varietal types and vintage year) on the wine rankings. We have restricted our analysis to wine samples to two red wine varietals (Cabernet Sauvignon and Merlot) and four countries (USA, Chile, Canada and Australia) due to time constraints. Additional wine samples can also be extracted for other related red-wine varietals (for example, Pinot Noir, Shiraz E) including European Countries. Consumers' purchasing decision is significantly affected by specific preferences towards well known wineries, available from the WS database. Modelling this feature would require advance data mining tools, such as support vector machine or neural network. The authors are at present working on these extensions.

REFERENCES

References available upon request from the corresponding author Mohua Podder (mohua1@ualberta.ca).