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Title: Hedonic Wine Price Predictions and Non Normal Errors

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Abstract: This paper considers using non normal error distributions for the hedonic wine price function, to predict -'average-' wine prices and hence identify over and under-priced wines. In addition to the log-normal distribution, the Weibull, gamma, exponential and log-logistic distributions are employed for a comprehensive data set of over 6,000 Australian wines. Estimates of marginal attribute impacts do differ with distribution employed with the Weibull being the most different. On average for all wines, the log-logistic distribution produces the most accurate predictions, however, the performance of distributions differs according to price range. Combining the predictions can produce substantially lower absolute errors on average, because of the varying accuracy performance of the distributions.

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1. Introduction

There is considerable on going interest in estimating the relation between the price of a bottle of wine and its characteristics. Wine lends itself particularly well to hedonic price estimation given the large number of unique individual wines available in any given market. One of the first published hedonic wine price functions was estimated for Australian wines more than 15 years ago, Oczkowski (1994). Coverage has now extended to wines produced and sold in countries and regions such as: Bordeaux, Spain, Burgundy, New Zealand, California, Italy, Washington, Piedmont, Bulgaria, South Africa, Sweden, Norway, United Kingdom and Chile. Additionally, extensions beyond the basic specification have examined issues such as: sensory vs objective characteristics (Lecocq and Visser, 2006) ; climate impact (Byron and Ashenfelter, 1995); geography and brand reputation (Schamel, 2006); measurement error (Oczkowski, 2001); structural change in price ranges (Costanigro, McCluskey and Mittelhammer, 2007); and investment ratings (Fogarty, 2006). The most cited papers in the literature include, Oczkowski (1994), Nerlove (1995), Combris, Lecocq and Visser (1997), Landon and Smith (1998) and Schamel and Anderson (2003). For a survey of some of the literature, see Fogarty (2003).

From the wine consumer's perspective, the price predictions from a hedonic wine function can be used as guide to identify bargains and expensive wines, Oczkowski (1994, p107). Essentially, if wines with similar characteristics (same quality, variety, etc) but with different prices are in the sample, then the hedonic price function predicts the 'average' price for these wines. Wines priced above this 'average' are over priced while those priced below the 'average' are under priced and represent good value for money. This information from the hedonic price function residuals can serve as a useful guide for consumer purchase decisions. [1]

From the wine producer's perspective accurately identifying the value of a bottle of wine relative to its competitors is important for correct price positioning (Oren, Smith and Wilson, 1984) and the potential exit of products from the market. As Stavins (1995) demonstrates for personal computers, the residuals from hedonic price functions can be incorprated into models of product exit. Stavins (1995) finds that overpricing, as identified through hedonic function residuals, does significantly explain the exit of products in the personal computer market. To this extent the identification of over priced wines may provide important information for wine producers.

The use of hedonic price functions to identify over and under pricing is feature of various studies. Van Rensburg and Priilaid (2004) use a linear hedonic framework to identify 'value' and 'expensive' price frontiers for South African red wines. Priilaid and van Rensburg (2006) use a non-linear function (dummy variables for all regressors) to identify the extent of 'mispricing' for South African wines. Applications of hedonic methods to identify over and underpricing in other areas include, Stavins (1995) for personal computers and Gergaud, Guzman and Verardi (2007) for Parisian gastronomic restaurants.

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[1] The *Australian Wine Price Calculator* (csusap.csu.edu.au/~eoczkows/winestart.htm) employs this methodology to make publicly accessible hedonic wine price research.

A feature of hedonic price predictions, is that some wines may be predicted to be very substantial bargains and some as very poor value for money, see Priilaid and van Rensburg (2006). The large size of some of these prediction errors may be considered ‘unrealistic’ for accurately valuing a bottle of wine and as such the use of these methods may have little practical value. Large prediction errors may be a result of numerous factors including, producer pricing strategies, omitted characteristics, the use of a single function for all wines and/or the use of the log-linear specification with normal errors. We make comment on each of these factors in turn.

Large wine producers may over or under price specific wines for strategic reasons. In a product line for a wine producer, significant under pricing for a wine may be the result of the marketing of a 'loss leader' wine, sold in larger volumes in order to establish greater related sales for higher priced wines for the producer. On the other hand, significant over pricing may occur as a producer attempts to infer quality through higher prices (Lambert, 1980). Secondly, large prediction errors may result from omitted characteristics for the estimated hedonic price function. To some extent all regression equations are suspect to claims of specification error. In our case, to make the results of research on price predictions publicly attractive, large data sets with numerous wines should be used in estimation, to incorporate the vast array of wines available in the market place. This to some extent limits the availability of potentially important characteristics to what is accessible in a single sourced wine guide which has consistent quality ratings.

Thirdly, large prediction errors may be the result of the use of a single price function for the entire data set, (Costanigro, McCluskey and Mittelhammer, 2007). On the other hand, a single estimated price function for all wines is useful as it provides a comprehensive evaluation of the concept of 'average', effectively using more information than less is desirable in deriving 'average' price predictions. What is unclear however and has not been previously researched for wine products, is the extent to which the assumption of normal errors affects price predictions. The use of non-normal errors for price predictions is the focus of this paper.

In particular we wish to investigate whether the use of non-normal errors significantly alters the marginal impacts on price of the typical quality, winery reputation, cellaring potential, vintage, variety and regional characteristics. Secondly, we will assess the predictive performance of models which assume non-normal errors and hence their ability to identify over and under priced wines. In the next section we outline the various non-normal error specifications to be considered. The sections thereafter present the hedonic wine price characteristics and data and then the estimated price functions and assessment of their predictive performance are outlined.

2. Non-Normal Error Distributions

The majority of estimated hedonic wine price functions (e.g., Oczkowski, 1994, 2001; Byron and Ashenfelter, 1995; Combris, Lecocq and Visser, 1997; Schamel and Anderson, 2003; Steiner, 2004; Lecocq and Visser, 2006; Fogarty, 2006; and Schamel 2006, 2009) have employed the log-linear specification using least squares as the estimator. We continue this tradition and employ a log-linear form but consider alternative distributions for the additive error term. In part, we make use of the generalized gamma distribution which encompasses various distributions. These types of log-linear non-normal models are frequently used in survival and duration analysis, for example Lawless (1982) and Lancaster (1990).

Employing the notational specification developed by Cameron and White (1990) we consider the following models for the price (P) of a bottle of wine:

$$\ln(P) = Y = X\beta + u \qquad (1)$$
$$\text{with} \quad u \sim iid\{(\exp[zk - \exp(z)]) / \sigma\Gamma(k)\} \qquad (2)$$
$$\text{where } z = (Y - X\beta)/\sigma \quad \text{and} \quad \sigma = 1/c$$

where, X are regressors with associated parameters β, u is an independently and identically distributed error term with the generalized gamma distribution, c and k are shape parameters and Γ is the gamma function. The generalized gamma distribution (with c > 0 and k > 0) encompasses four other distributions: 1) c = 1 and k > 0 the simple gamma distribution; 2) k = 1 and c > 0 the Weibull distribution; 3) c = k = 1 the exponential distribution; and 4) c > 0 and $k \to \infty$ the normal distribution. The latter model is often termed the 'log-normal' model and can be simply estimated via least squares using the log of P as the dependent variable.

In addition to the generalized gamma set of models we also consider the log-logistic specification. This specification is also commonly employed in survival and duration studies, for example Addison and Portugal (1987) and Swaim and Podgursky (1992). The log-logistic model also maintains the log-linear additive error term form of equation (1) but with the error term:

$$u \sim iid\{\exp(z)/(\sigma[1+\exp(z)]^2)\} \qquad (3)$$

Since all models have the log-linear form then β will be comparable across specifications and have the standard approximate percentage change interpretation.

Maximum likelihood is used for estimation using the Gauss 8.0 software. Two optimisation algorithms are employed i.e., the Newton-Raphson and the Broyden, Fletcher, Goldfarb, Shanno methods. Various starting points are utilised to ensure that local maximums have been reached. The inverse of the estimated Hessian matrix is used to construct the standard errors of the parameters.

When constructing price predictions from these models we need to recognise that $E\{\exp(u)\} \neq 1$ and that some adjustment is needed to $\exp(X\hat{\beta})$ in generating predictions for exp(Y) or price. For the generalized gamma distribution we have (see McDonald (1984)):

$$E(P) = E\{\exp(Y)\} = E\{\exp(X\beta)\exp(u)\} = \exp(X\beta)\{\Gamma(k+\sigma)/\Gamma(k)\} \quad (4)$$

Thus for the various models we generate predictions for price using: 1) $\hat{P} = \exp(X\hat{\beta})\hat{k}$ for the simple gamma; 2) $\hat{P} = \exp(X\hat{\beta})\Gamma(1+\hat{\sigma})$ for the Weibull; 3) $\hat{P} = \exp(X\hat{\beta})$ for the exponential; and 4) $\hat{P} = \exp(X\hat{\beta})\exp(\hat{\sigma}^2/2)$ for the log normal. For generating price predictions for the log-logistic we use (see Kalbfleisch and Prentice (1980)): $\hat{P} = \exp(X\hat{\beta})\Gamma(1+\hat{\sigma})\Gamma(1-\hat{\sigma})$.

3. Hedonic Price Function Specification and Data

In an attempt to achieve the widest coverage of wines we employ James Halliday's *Australian Wine Companion* which reports information on over 6000 wines annually. This guide has previously been employed by Schamel and Anderson (2003). The alternative of using multiple wine guides suffers from the inconsistency of employing wine quality scores from differ tasters. To some extent the information in the *Australian Wine Companion* dictates the types of characteristics to be employed in the function. The broad specification employed is:

$$\ln(\text{Price}) = f(\text{quality scores, winery reputation, cellaring potential, vintage, variety, region}) \quad (5)$$

This specification captures the majority of characteristics found to be important in previous studies. Quality scores were first employed by Oczkowski (1994) and continue to be one of the dominant regressors in hedonic wine price functions. Winery reputation has been used by Schamel and Anderson (2003) and Schamel (2006, 2009) and captures the overall reputation of a winery and its ability to produce a range of high quality wines. Cellaring potential and vintage capture the time value of the wine, while location and type characteristics are captured by the wine regional and varietal variables.

The first three characteristics in equation (5) are 'subjective', the last three 'objective'. In terms of the linear specification of the regressors, dummies must be employed for the objective characteristics as the sample includes non-vintage wines. For the subjective attributes at least two possibilities exist, the use of dummies as in

Oczkowski (1994) or the use of single continuous variables as in other studies such as Combris, Lecocq and Visser (1997) and Schamel and Anderson (2003). To some extent the use of continuous variables is restrictive as they assume a constant marginal percentage impact throughout the entire range of the variables. This is particularly restrictive at the extreme ends of variables where significant under and over price predictions may prevail. Our initial estimation indicated the superior performance of dummy variables for the subjective attributes both in terms of the accuracy of price predictions and the non-linear nature marginal impacts.

Table 1 About Here

The data refers to the 2008 edition of the wine guide and consists of 6497 evaluated wines.[2] Descriptive statistics are provided in table 1. Details on specific vintages, varieties and regions are provided with the estimates in table 2. The ratio of the skewness and kurtosis coefficients to their standard errors for price are 125.7 and 372.5 respectively, which indicates significant positive skewness and a very sharp peak. This shape is confirmed by the price quartiles of: 4.59 (0%), 17.50 (25%), 20.75 (50%), 27.00 (75%) and 200 (100%). This is the typical distribution for wine prices and explains the predominance of the log-linear (log-normal) over the linear (normal) form in hedonic wine studies.

4. Hedonic Price Function Estimates and Price Predictions

In this section we present the results of the estimation of equation (5) using the various error distributions described in equations (2) and (3). Two difficulties were encountered in estimation. First, it was not possible to gain meaningful estimates for the generalized gamma distribution. Non-convergence of the log-likelihood function

[2] We thank Mr James Halliday for making the data set electronically accessible.

occurred using various algorithms and starting values as $k \rightarrow \infty$ consistently. Non-convergence problems with the generalized gamma distribution were also encountered in some of the models estimated by Cameron and White (1990). Even performing a grid search fixing k at various values and freely estimating only β and 'c' as suggested by Lawless (1982) also failed to identify a unique local maximum log-likelihood. As a consequence no meaningful estimates of the generalized gamma model can be provided.

The second estimation issue pertains to the identical estimates emanating from the simple gamma (c = 1) and the exponential (c = k = 1) models. Identical β's were gained except for a smaller constant for the gamma model. A similar finding occurred for the Cameron and White (1990) models. Further, the price predictions using the expressions described in section two were identical for the two models. It transpires that the smaller constant for the gamma model exactly off-sets the 'k' adjustment for the gamma model to produce identical predictions to the exponential model. The only difference in the models are the smaller standard errors produced by the gamma model resulting in a larger number of significant regressors. As a consequence we report only one set of estimates for the gamma/exponential models and identify significant regressors based on the gamma estimates.

Table 2 About Here

The parameter estimates[3] for the log-normal, Weibull, gamma/exponential and log-logistic models are presented in table 2. Irrespective of the distribution employed the

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[3] Control variables are denoted in the table for each variable set, to some extent the identified significant regressors are arbitrary as an alternative choice of control variable produces different results. For ease of interpretation, the categories with the highest frequency of wines were chosen as the control variables. For variety (Shiraz) and region (Barossa Valley) the controls coincide with Schamel and Anderson (2003).

following general results emerge. As expected, a higher price is predicted: the higher the quality rating score, the higher the winery reputation, the longer the cellaring potential and the older the vintage. Even though these findings are not always strictly monotonic they hold in general.[4] There appears to be wide variability in the variety and regional impacts but the major consistent positive price impacts can be identified as: Muscat, Tokay, other Red Varietals; and East Coast Tasmania, Southern Tasmania and South Burnett. The major consistent negative price varietal and regional impacts are: Semillon/Chardonnay, Frontignac, Cabernet Franc blends; and Riverina, Goulburn Valley and Riverland.

There are some important differences in the marginal percentage impacts between the distribution assumptions. In a broad sense, for all variables except cellar potential, the Weibull distribution generally produces the largest impacts followed by the gamma/exponential model, the log-normal and finally the log-logistic distribution. This order of magnitude is clearest for the impact of winery reputation. For rating, vintage, variety and region the order of the distributions holds only in a general sense. For cellar potential in general the order of the largest impacts is reversed with the log-logistic producing the largest and Weibull the smallest. Some of the differences in

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[4] We comment on the non-linearity of the rating, winery reputation and cellaring potential results and hence the preference for the use of dummies over continuous variables. Irrespective of which distribution is employed it is clear that the distance between the various rating, winery reputation and cellaring points is not constant, for example, disproportionately large increases occur when moving from a rating of 96 to 97, for a winery reputation of 4 to 4.5, and from a cellar date of 2033 to 2034. Further, even though there is a general finding of the higher the rating, the higher the winery reputation and the longer the cellaring potential the higher the price these relations are not always monotonic, for example there is a fall in marginal impact in moving from a rating of 80 to 81, from a winery reputation of 2.5 to 3 and in moving from a cellar potential of 2034 to 2035.

estimated impacts are substantial, especially at the extremes of the variables. For example, for a quality rating of 97 (compared to the control score of 90) Weibull suggests a 114% discount, while the log-normal, gamma/exponential and log-logistic models estimate discounts 82%, 92% and 77%, respectively.

Our results are most comparable with Schamel and Anderson (2003) who, in part, also used the Halliday data covering the years 1992 to 2000. In comparing our log-normal results we find that the wine quality impact has increased, for a one point increase Schamel and Anderson (2003) estimate impacts of 2.3% to 4.1%, our impact averages 6.4%. In contrast, our average one point increase in winery reputation of 0.8% is significantly lower than Schamel and Anderson's (2003) estimates of 2.1% to 9.3%. This may imply that compared to the 1990s, the quality of the particular wine is of increasing importance, while the reputation of the winery is of weakening importance for price impacts. Compared to Schamel and Anderson (2003) our results show the weakening impact of the dominant variety (Shiraz) and the improving impact of the dominant region (Barossa Valley). In Schamel and Anderson (2003) for the majority of years Shiraz was estimated to have the greatest positive impact, while for 1997 to 2000 in general, Barossa Valley had the weakest price impact of the regions. For our comparable log-normal results, now only 54% of regions have a smaller varietal impact than Shiraz and only 30% of regions have a larger regional impact than the Barossa Valley.

Given the extensive coverage of the employed data set we are able to identify with greater specificity varietal and regional impacts. In terms of price premiums for regions, cool climate regions as expected, such as East Coast Tasmania and Southern

Tasmania stand out, but also South Burnett a region in the relatively warm state of Queensland commands a premium. For varietals price premiums have been identified for some major variates such as Malbec and Pinot Gris, but also for a range of minor varieties such as: Nebbiolo, Viognier and Zinfandel. Also varieties not produced in significant volumes (Arneis) or identified as non-premium grapes (Grenache) command price premiums (see Jackson, 2009).

Table 3 About Here

The accuracy measures for the predictions[5] from these models (using the expressions described in section 2) are presented in table 3. Absolute, squared and percentage based measures of predictive performance are provided for all wines and for the four quartile ranges when wines are ordered by price. In particular we measure: mean error (ME), mean absolute error (MAE), mean square error (MSE), mean absolute percentage error (MAPE), mean square percentage error (MSPE), percentage of positive errors (PPE), and the percentage of minimum absolute errors for the distribution (PMAE).

For all wines, the log-logistic model has the smallest MAE, MPAE and MSPE, while the gamma/exponential model has the smallest MSE. In terms of the model which

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[5] The predictions are generated using, $\hat{P} = \exp(X\hat{\beta})\,\alpha$ with the estimated adjustments (α) being: 1.0414, 0.8949, 11.827, 1.0, 1.0385 for log-normal, Weibull, gamma, exponential and log-logistic, respectively. As a further alternative we considered the least squares log-linear model with a consistent estimate of the adjustment factor which does not assume normality, see Wooldridge (2006, pp 219-220). The approach uses the log-normal parameter estimates with an adjustment factor of 1.0679. This consistent 'distribution free' approach produced worse MAE (5.99), MAPE (23.8) and MSPE (255.7) than the log-normal model and a similar MSE (106.6) and hence is not considered any further.

has the lowest number of absolute (or squared) errors (PMAE) the log-logistic is best 42% of the time followed by the Weibull with 35%.

The quartiles illustrate some interesting features. The MEs and PPEs reflect the general notion that prices are over predicted (by about 30% on average) for low price wines ($P \leq \$17$) and under-predicted (by about 25% on average) for high price wines ($P \geq \$27$).[6] For each of the three lowest quartiles ($P < \$27$) the log-logistic has smallest MAE, MSE, MAPE and MSPE values. For the highest quartile ($P \geq \$27$) the Weibull is best for MAE, MSE and MSPE, while the gamma/exponential is best for MAPE.

The performance of the Weibull distribution requires special comment. In terms of the measures MAE, MSE, MAPE and MSPE, the Weibull performs poorest in all cases (bar one) for all wines and in all quartiles except for the highest price quartile. These measures contrast to PMAE where the Weibull produces the lowest number of absolute errors for the lowest and highest price quartiles and the second lowest number of absolute errors for the middle two price quartiles. In essence the Weibull predictions tend to be close or far away and hence in terms of the average measures (especially MSE and MSPE) it performs relatively poorly. These results reflect some of differences in parameter estimates identified in table 2 between the Weibull and other distributions.

[6] These over and under predicted prices at the extreme ends of price ordered data sets are expected by definition as numerous wines with similar quality scores appear in data sets and hence those with the lowest (highest) prices are deemed to be significantly under (over) priced.

An important issue is whether there is any significant difference between the predictive performance of the various models. A causal examination of the various measures in table 3 suggests reasonably similar performance between the alternative error distributions, however, this may be masked by the fact that only average prediction measures are considered. We employ the Diebold and Mariano (1995) accuracy difference test to examine whether there are statistically significant differences between the predictors[7]. The results in table 4 indicate that significant pairwise differences exist for all comparisons when using MAE, MAPE and MSPE. While for MSE only two of the five differences are not significant. The different predictions from the models can be further illustrated by some examples in table 5. In general, even though most of the predictions produced by the models are similar, these examples have been selectively chosen to illustrate that large predictions differences can be produced by the different error distributions.

Tables 4 & 5 About Here

Given the existence of some differences in price predictions a natural question to ask is whether combining these predictions can produce significantly superior predictions? This might be considered important given that the MAPEs could be considered large, ranging from about 15% to 30% depending on the price quartile.[8] A

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[7] We employ the S_1 test in Diebold and Mariano (1995) which tests whether $d = g(e_1) - g(e_2)$ is significantly different from zero, where e_i i =1,2 are errors from alternative predictors. In our case we follow Clark (1999) and test for significance of α in the regression of d = α + error, using the Newey-West HAC estimator. For g(.) we employ MAE, MSE, MAPE and MSPE.

[8] Whether these prediction errors are too large is an interesting issue. It could be argued that having large errors is useful as it allows the consumer to identify particularly attractive bargains or 'over-priced wines', reducing the size of these errors limits these possibilities. It may be suggested that as long as the notion of 'average hedonic' price prediction is maintained whether a particular wine is substantially over or under priced is not an issue to be concerned about.

general review of combining forecasts is provided by Clemen (1989). Our focus is exclusively on combining in-sample predictions rather than post-sample forecasts, to this extent some of the literature on combining forecasts is not relevant. We investigated regression based approaches to combining predictions (Granger and Ramanathan (1984)) but these methods invariably produced some negative weights and some combined predictions which were negative! Methods which used changing weights based on multiple structural breaks (Bai and Perron (2003), to recognise the varying performance of the distributions) were employed, but also resulted in some negative weights and price predictions.[9]

As an alternative to using regression methods for combining predictions, table 3 also reports a combined forecast which chooses the distribution with the smallest absolute (or squared) error for each wine. The frequency of each distribution which makes up this combined forecast is given by the PMAE measure in table 3. The Weibull and log-logistic distributions contribute most to the combined predictor. The relative importance of the distributions varies over the different price quartiles. In terms of the various performance measures the combined predictor provides a substantial improvement. In terms of MAPE the improvement is about 5% and for MSPE from about 20% to 100%.

5. Conclusions

This paper has examined the use of non-normal errors in hedonic wine price functions. In general it appears that alternative error distributions do make a

[9] To explicitly capture the possible varying performance of models over different price ranges we estimated various quantile regression models, these invariably produced inferior predictions to the non-normal distributions.

difference to both marginal impact estimates and price predictions. The general results about quality scores, winery reputation, cellar potential and vintages are maintained but the magnitudes of the impacts varies between error distributions.

In terms of predictions it appears that overall the log-logistic distribution produces the most accurate predictions, however, the relative performance of the distributions appears to depend on the price range examined. The standard log-normal distribution is not always the most accurate form for estimating the hedonic wine price function. Combining the predictions can produce substantially lower absolute errors on average, this occurs because of the varying accuracy performance of the models over the different price ranges. These predictions may provide important information for consumers in more accurately identifying bargain and expensive wines and for producers in identifying important price points and removing over priced wines from the market.

Finally, our results provide important contemporary information about the Australian wine market. It would appear that the impact of the specific quality of the wine is gaining more importance at the expensive of the reputation of the wine producer *per se*. Further some new regions and varieties have been identified as attracting price premiums, this recognition may open up some important longer-term investment opportunities for producers.

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Table 1: Descriptive Statistics

	Mean	Std Dev	Min	Max
Price ($AUD)	24.71	14.19	4.59	200
Quality Rating (max 100)	89.69	3.20	77	97
Cellaring Potential (best 'drink to' year)	2012.1	5.14	2007	2039
Winery Reputation (max 5)	4.38	0.62	2.5	5
Vintage	13 vintages and a non-vintage			
Variety	78 varieties			
Region	88 regions			

Table 2
Hedonic Wine Price Function Parameter Estimates

	Log-Normal	Weibull	Gamma / Exponential	Log-Logistic		Log-Normal	Weibull	Gamma / Exponential	Log-Logistic
Constant	3.066*	3.406*	0.680*/ 3.151*	3.012*	**Shape Parameters** (σ and k)	0.285*	0.318*	11.83*	0.151*
Rating (0-100)					**Vintage** (year)				
97	0.858*	0.843*	0.866*	0.918*	2006	control	control	control	control
96	0.551*	0.586*	0.581*	0.592*	2005	-0.042*	-0.066*	-0.046*	-0.042*
95	0.306*	0.354*	0.331*	0.309*	2004	0.074*	0.083*	0.081*	0.067*
94	0.149*	0.169*	0.159*	0.136*	2003	0.192*	0.242*	0.217*	0.169*
93	0.079*	0.202*	0.110*	0.053*	2002	0.140*	0.130*	0.151*	0.149*
92	0.047*	0.094*	0.058*	0.032*	2001	0.340*	0.548*	0.409*	0.284*
91	0.010	-0.012	0.006	0.013	2000	0.439*	0.601*	0.534*	0.391*
90	control	control	control	control	1999	0.214*	0.198	0.224*	0.296*
89	-0.024	-0.024	-0.023	-0.026*	1998	0.520*	0.771*	0.694*	0.498*
88	-0.072*	-0.072*	-0.073*	-0.068*	1997	0.577*	0.585*	0.602*	0.544*
87	-0.070*	-0.075*	-0.075*	-0.064*	1996	0.263	0.147	0.224	0.219
86	-0.143*	-0.130	-0.143*	-0.149*	1995	1.085*	0.829*	1.023*	1.083*
85	-0.163*	-0.129	-0.154*	-0.157*	1993	-0.063	-0.128	-0.054	-0.113
84	-0.231*	-0.220*	-0.228*	-0.217*	NV	-0.050	0.097*	-0.005	-0.088
83	-0.244*	-0.202*	-0.232*	-0.244*					
82	-0.198	-0.186	-0.203	-0.192	**Cellar** (drink)				
81	-0.335	-0.305	-0.335	-0.341*	2039	0.459	0.178	0.350	0.452
80	-0.161	-0.194	-0.176	-0.175	2037	1.460*	1.073*	1.310*	1.523*
79	-0.132	-0.208	-0.166	-0.124	2035	0.237	0.003	0.179	0.263
77	-0.822*	-1.140*	-0.920*	-0.767*	2034	1.034*	1.165*	1.141*	1.230*
					2033	0.497*	0.211	0.397	0.537*
Winery Reputation (0-5)					2031	0.780*	0.502*	0.725*	0.990*
5	control	control	control	control	2030	0.488*	0.482*	0.491*	0.541*
4.5	-0.052*	-0.097*	-0.066*	-0.040*	2029	0.577*	0.562*	0.588*	0.590*
4	-0.080*	-0.137*	-0.100*	-0.067*	2028	0.620*	0.723*	0.700*	0.646*
3,5	-0.085*	-0.135*	-0.099*	-0.070*	2027	0.331*	0.213	0.304*	0.341*
3	-0.095*	-0.134*	-0.106*	-0.086*	2026	0.230*	0.182	0.204*	0.210*
2.5	-0.038	-0.126*	-0.062	-0.032*	2025	0.345*	0.346*	0.352*	0.355*
					2024	0.331*	0.295*	0.330*	0.344*
					2023	0.291*	0.207*	0.275*	0.350*
					2022	0.358*	0.312*	0.357*	0.394*
					2021	0.285*	0.170*	0.249*	0.273*
					2020	0.241*	0.308*	0.253*	0.225*
					2019	0.202*	0.177*	0.194*	0.211*
					2018	0.126*	0.047	0.105*	0.141*
					2017	0.233*	0.258*	0.239*	0.217*
					2016	0.144*	0.141*	0.141*	0.131*
					2015	0.184*	0.199*	0.187*	0.178*
					2014	0.140*	0.152*	0.143*	0.134*
					2013	0.148*	0.188*	0.154*	0.136*
					2012	0.118*	0.107*	0.116*	0.120*
					2011	0.078*	0.075*	0.078*	0.081*
					2010	0.060*	0.077*	0.062*	0.055*
					2009	0.030	0.002	0.023	0.036*
					2008	control	control	control	control
					2007	0.080	0.045	0.074	0.093*

Table 2 ctd
Hedonic Wine Price Function Parameter Estimates

	Log-Normal	Weibull	Gamma / Exponential	Log-Logistic		Log-Normal	Weibull	Gamma / Exponential	Log-Logistic
Variety					**Variety**				
Arneis	0.111	0.003	0.086	0.133	Other Fortified	-0.119	-0.312*	-0.183	-0.052
Barbera	-0.037	-0.217*	-0.082	-0.045	Other Red Varieties	0.305*	0.216*	0.291*	0.366*
Botrytis	0.129*	-0.007	0.091	0.164*	Other White Varieties	0.097	0.168	0.124	0.079
Cabernet Blends	-0.021	-0.083	-0.030	-0.007	Petit Verdot	0.020	-0.049	-0.002	0.047
Cabernet Franc	0.029	0.065	0.032	0.007	Pinot Grigio	0.034	-0.069	0.006	0.046
Cabernet Franc Blend	-0.053	0.073	-0.016	-0.121	Pinot Gris	0.106*	0.032	0.089*	0.119*
Cabernet / Malbec	-0.227	-0.421*	-0.284*	-0.156	Pinot Noir	0.146*	0.148*	0.148*	0.144*
Cabernet / Merlot	-0.141*	-0.224*	-0.164*	-0.116*	Port	0.109*	0.210*	0.171*	0.099
Cabernet /Merlot Blend	0.076	-0.084	0.038	0.124	Red Blends	0.010	-0.088	-0.009	0.030
Cabernet Sauvignon	-0.039*	-0.077*	-0.056*	-0.024	Riesling	-0.200*	-0.285*	-0.221*	-0.169*
Cabernet Sauvignon/ Franc / Merlot	-0.129	0.021	-0.050	-0.009	Rose	-0.098*	-0.188*	-0.120*	-0.079*
Cabernet / Shiraz	-0.097*	-0.010	-0.067	-0.137*	Roussanne	0.026	-0.090	-0.004	0.039
Cabernet/ Shiraz/Merlot	-0.188*	-0.282*	-0.213*	-0.179*	Sangiovese	0.021	-0.090	-0.010	0.044
Chambourcin	0.068	-0.005	0.049	0.072	Sangiovese Blend	0.076	-0.003	0.060	0.087
Chardonnay	-0.013	-0.084*	-0.031	0.001	Sauvignon Blanc	-0.023	-0.115*	-0.047	-0.008
Chardonnay Unwooded	-0.128*	-0.224*	-0.151*	-0.107*	Sauvignon Blanc Blend	-0.181	-0.225	-0.191	-0.176*
Chardonnay / Viognier	-0.096	-0.213	-0.121	-0.078	Sauvignon / Semillon	-0.103*	-0.222*	-0.135*	-0.087*
Chenin Blanc	-0.083	-0.175*	-0.110	-0.074	Semillon	-0.257*	-0.316*	-0.274*	-0.222*
Durif	0.081	0.001	0.053	0.103*	Semillon Blend	-0.129	-0.189	-0.138	-0.129
Fortified Shiraz	-0.128	-0.289*	-0.166	-0.094	Semillon / Chardonnay	-0.389*	-0.513*	-0.420*	-0.371*
Frontignac	-0.266*	-0.337*	-0.283*	-0.259*	Semillon / Sauvignon	-0.465*	-0.247*	-0.190*	-0.149*
Gamay	0.096	0.018	0.074	0.098	Shiraz	control	control	control	control
Gewurztraminer	-0.038	-0.164*	-0.072	-0.029	Shiraz Blends	-0.050	-0.104	-0.062	-0.050
Grenache	0.201*	0.217*	0.209*	0.178*	Shiraz / Cabernet	-0.177*	-0.117*	-0.171*	-0.178*
Grenache Blends	0.018	-0.172*	-0.030	0.057	Shiraz / Grenache	-0.140	-0.348*	-0.198*	-0.105
Grenache / Shiraz	-0.229	-0.360*	-0.257*	-0.166*	Shiraz / Grenache /Mourvedre	-0.093	-0.325*	-0.159	-0.028
Grenache / Shiraz / Mourvedre	-0.041	-0.146	-0.050	-0.021	Shiraz / Viognier	-0.102*	-0.178*	-0.124*	-0.077*
Malbec	0.177	0.143	0.181	0.226*	Sparkling Red	0.160*	0.011	0.121*	0.205*
Marsanne	-0.043	-0.163*	-0.072	-0.026	Sparkling Rose	0.243	0.225	0.256	0.348*
Marsanne Roussane	-0.001	-0.157	-0.040	0.015	Sparkling White	0.127*	0.097*	0.107*	0.162*
Marsanne Viognier	-0.041	-0.215	-0.100	0.001	Sweet White	-0.074	-0.160*	-0.096*	-0.039
Merlot	-0.029	-0.100*	-0.047*	-0.015	Tempranillo	0.086*	-0.001	0.065	0.091*
Merlot Blends	-0.081	-0.267*	-0.122	-0.079	Tempranillo Blend	0.117	-0.040	0.081	0.157
Merlot / Cabernet Sauvignon	-0.166	-0.263*	-0.189	-0.151	Tokay	0.374*	0.375*	0.383*	0.341*
Merlot/Cabernet Franc	0.033	-0.078	0.001	0.048	Verdelho	-0.023	-0.110*	-0.044	-0.017
Moscato	-0.067	-0.185	-0.091	-0.030	Viognier	0.177*	0.104*	0.162*	0.179*
Mourvedre	0.099	-0.098	0.065	0.136	Viognier Blend	0.042	-0.048	0.011	0.052
Muscat	0.401*	0.572*	0.472*	0.365*	White Blends	-0.167*	-0.214*	-0.176*	-0.149*
Nebbiolo	0.238*	0.277*	0.245*	0.204*	Zinfandel	0.318*	0.165	0.278*	0.362*

Table 2 ctd
Hedonic Wine Price Function Parameter Estimates

Region	Log-Normal	Weibull	Gamma / Exponential	Log-Logistic	Region	Log-Normal	Weibull	Gamma / Exponential	Log-Logistic
Adelaide Hills	-0.045	-0.203*	-0.082*	-0.008	King Valley	-0.034	-0.170*	-0.065*	-0.017
Adelaide Plains	-0.031	-0.152*	-0.057	-0.013	Langhorne Creek	-0.137*	-0.330*	-0.181*	-0.102*
Adelaide Zone	-0.060	0.145	0.038	-0.172	Limestone Coast Zone	-0.253*	-0.395*	-0.288*	-0.206*
Albany	-0.201*	-0.469*	-0.267*	-0.142*	Lower Hunter Valley	0.025	-0.077*	0.003	0.057*
Alpine Valleys	0.006	-0.094	-0.024	0.030	Macedon Ranges	0.052	-0.028	0.030	0.091*
Ballarat	-0.038	-0.192*	-0.071	0.026	Manjimup	-0.107	-0.331*	-0.162	-0.067
Barossa Valley	control	control	control	control	Margaret River	-0.007	-0.136*	-0.036	0.020
Beechworth	0.146*	-0.053	0.103	0.186*	McLaren Vale	-0.094*	-0.143*	-0.104*	-0.068*
Bellarine Peninsula	-0.115	-0.254*	-0.143*	-0.082	Mornington Peninsula	0.083*	-0.100*	0.042	0.120*
Bendigo	-0.081*	-0.300*	-0.135*	-0.043	Mount Barker	-0.183*	-0.366*	-0.228*	-0.146*
Big Rivers Zone	-0.291*	-0.521*	-0.340*	-0.280*	Mount Benson	-0.158*	-0.352*	-0.203*	-0.109*
Blackwood Valley	-0.174*	-0.328*	-0.210*	-0.159*	Mount Burnett	0.204	-0.003	0.150	0.242*
Canberra District	0.058	-0.036	0.039	0.082*	Mount Gambier	-0.225	-0.445*	-0.279*	-0.198*
Central Ranges Zone (NSW)	-0.278*	-0.419*	-0.308*	-0.226*	Mudgee	-0.025	-0.178*	-0.057	0.006
Central Victoria Zone	0.001	-0.255*	-0.061	0.032	Murray Darling	-0.312*	-0.464*	-0.344*	-0.301*
Clare Valley	-0.043	-0.209*	-0.082*	-0.011	Nagambie Lakes	-0.280*	-0.388*	-0.291*	-0.277*
Coonawarra	0.011	-0.112*	-0.012	0.019	New England	-0.148*	-0.348*	-0.194*	-0.125*
Cowra	-0.056	-0.206*	-0.087	-0.026	Northern Tasmania	0.056	-0.088*	0.026	0.099*
Darling Downs	-0.076	-0.275	-0.129	-0.050	Orange	0.012	-0.156*	-0.028	0.046
Denmark	-0.010	-0.218	-0.062	0.027	Padthaway	-0.145*	-0.234*	-0.150*	-0.142*
East Coast Tasmania	0.230*	0.158	0.222*	0.214*	Peel	-0.159*	-0.345*	-0.205*	-0.119
Eden Valley	-0.022	-0.182*	-0.059	0.007	Pemberton	-0.145*	-0.287*	-0.180*	-0.106*
Frankland River	-0.143*	-0.283*	-0.176*	-0.096*	Perth Hills	0.010	-0.149*	-0.022	0.029
Geelong	0.031	-0.113*	-0.001	0.061*	Porongurp	-0.037	-0.223*	-0.081	0.004
Geographe	-0.089*	-0.224*	-0.123*	-0.067	Port Phillip Zone	-0.220*	-0.425*	-0.276*	-0.187*
Gippsland	0.065*	0.049	0.056	0.084*	Pyrenees	-0.015	-0.132*	-0.038	0.013
Glenrowan	-0.157*	-0.275*	-0.186*	-0.122*	Queensland Coastal	0.117	-0.051	0.081	0.161*
Goulburn Valley	-0.345*	-0.486*	-0.387*	-0.328*	Queensland Zone	-0.060	-0.283*	-0.110	-0.017
Grampians	0.001	-0.148*	-0.042	0.036	Riverina	-0.492*	-0.570*	-0.495*	-0.474*
Granite Belt	0.032	-0.109*	0.002	0.061	Riverland	-0.360*	-0.457*	-0.374*	-0.347*
Great Southern	-0.175*	-0.403*	-0.235*	-0.135*	Rutherglen	-0.099*	-0.270*	-0.131*	-0.062
Greater Perth Zone	-0.144	-0.310*	-0.182	-0.093	Shoalhaven Coast	0.062	-0.101	0.024	0.076
Gundagai	-0.110	-0.308*	-0.167	-0.075	South Australia	-0.230	-0.413*	-0.269*	-0.178
Heathcote	0.085*	-0.020	0.070*	0.112*	South Burnett	0.152*	0.001	0.114	0.168*
Henty	-0.053	-0.264*	-0.107	-0.013	Southeast Australia	-0.271*	-0.440*	-0.313*	-0.255*
Hilltops (NSW)	-0.105	-0.319*	-0.158*	-0.057	Southern Fleurieu	-0.110*	-0.283*	-0.150*	-0.053
Kangaroo Island	0.001	-0.099	-0.002	-0.016	Southern Flinders Ranges	-0.208	-0.450*	-0.269*	-0.177

Table 2 ctd
Hedonic Wine Price Function Parameter Estimates

	Log-Normal	Weibull	Gamma / Exponential	Log-Logistic		Log-Normal	Weibull	Gamma / Exponential	Log-Logistic
Region					**Region**				
Southern Highlands	0.001	-0.196*	-0.045	0.037	Tumbarumba	0.022	-0.162	-0.021	0.062
Southern Tasmania	0.185*	0.065	0.155*	0.208*	Upper Goulburn	-0.037	-0.197*	-0.071	0.011
Strathbogie Ranges	-0.073	-0.042	-0.061	-0.055	Upper Hunter Valley	-0.104*	-0.171*	-0.122*	-0.102*
Sunbury	-0.008	-0.178*	-0.043	0.051	Warehouse	-0.169	-0.136	-0.104	0.037
Swan District	-0.227*	-0.356*	-0.253*	-0.180*	Western Plains Zone (NSW)	-0.084	-0.211*	-0.108	-0.050
Swan Hill	-0.339*	-0.519*	-0.380*	-0.297*	Wrattonbully	-0.002	-0.095	-0.016	0.019
Swan Valley	-0.167*	-0.284*	-0.189*	-0.129*	Yarra Valley	0.012	-0.153*	-0.025	0.045*

* Denotes significant at the 5% level. N = 6497. Dependent variable: ln (Price), mean = 3.1062

Table 3
Hedonic Wine Price Predictions Accuracy Measures

	ME	MAE	MSE	MAPE	MSPE	PPE	PMAE
All Wines (N=6497)							
Log-Normal	0.27	5.85	107.1	22.7	243.0	41.0	13.3
Weibull	-0.29	6.32	103.8	25.7	301.9	46.4	35.3
Gamma/Exponential	0.04	5.90	103.4	23.3	255.0	42.7	9.1
Log-Logistic	0.65	5.77	110.5	21.9	241.4	42.5	42.3
Combined	0.33	4.71	77.8	18.3	182.6	44.1	100
\$17 > P (N = 1394)							
Log-Normal	-4.10	4.35	32.4	32.7	242.6	10.6	6.7
Weibull	-3.81	4.56	45.1	34.3	334.3	23.6	46.1
Gamma/Exponential	-4.03	4.37	35.4	32.9	265.0	13.8	8.7
Log-Logistic	-3.94	4.18	29.8	31.5	225.0	10.2	38.5
Combined	-3.21	3.48	24.9	26.4	188.5	16.9	100
\$17 ≤ P ≤ \$20 (N = 1851)							
Log-Normal	-2.88	3.76	26.4	20.1	141.0	26.4	9.1
Weibull	-2.61	4.53	42.1	24.1	224.1	39.3	31.1
Gamma/Exponential	-2.80	3.91	29.8	20.8	159.0	30.8	8.7
Log-Logistic	-2.62	3.45	22.5	18.4	120.1	26.2	51.1
Combined	-2.16	2.94	19.4	15.7	103.6	32.0	100
\$20 < P < \$27 (N = 1596)							
Log-Normal	-1.04	3.95	29.8	16.7	127.2	47.0	18.7
Weibull	-1.33	5.29	54.5	22.4	231.5	49.9	22.1
Gamma/Exponential	-1.15	4.30	36.5	18.2	155.4	48.3	6.8
Log-Logistic	-0.66	3.64	27.2	15.4	116.1	50.3	52.4
Combined	-0.64	3.24	23.4	13.7	99.8	49.6	100
\$27 ≤ P (N = 1656)							
Log-Normal	8.76	11.3	334.4	23.0	469.2	77.2	18.4
Weibull	6.25	10.8	269.6	23.6	429.3	70.2	43.7
Gamma/Exponential	7.80	11.0	307.4	22.9	450.0	74.7	12.0
Log-Logistic	9.42	11.7	357.3	24.0	511.5	80.6	25.9
Combined	7.04	9.14	240.0	18.7	345.9	75.2	100

ME: mean error, MAE: mean absolute error, MSE: mean square error, MAPE: mean absolute percentage error, MSPE: mean square percentage error, PPE: percentage of positive errors, PMAE: percentage of minimum absolute errors for the distribution. Error = P - $\hat{P}$.

Table 4
Hedonic Wine Price Predictions:
Diebold-Mariano Accuracy Difference Tests

Difference	**MAE**	**MSE**	**MAPE**	**MSPE**
Log Normal – Weibull	-0.470* (-10.1)	3.290 (1.03)	-0.030* (-17.9)	-0.588* (-9.97)
Log Normal – Gamma/Expo	-0.051* (-2.96)	3.658* (2.72)	-0.006* (-10.8)	-0.120* (-5.51)
Log Normal – Log Logistic	0.085* (5.52)	-3.493* (-3.13)	0.008* (14.7)	0.017 (0.88)
Weibull – Gamma/Expo	0.419* (13.1)	0.368 (0.19)	0.024* (20.0)	0.468* (11.7)
Weibull – Log Logistic	0.555* (10.2)	-6.783* (-1.96)	0.038* (19.0)	0.605* (9.44)
Gamma/Expo – Log Logistic	0.136* (5.31)	-7.151* (-4.49)	0.014* (15.20)	0.137* (5.14)

Figures represent differences and numbers in parentheses the test statistics distributed as N(0,1). * denotes significance at the 5% level.

Table 5
Hedonic Wine Price Example Predictions

Price ($)	Log-Normal	Weibull	Gamma/ Exponential	Log-Logistic
180	78.50	111.23	92.90	88.42
150	112.81	156.23	133.99	136.13
64.95	67.75	93.30	77.74	65.53
47	40.13	51.44	43.31	36.47
34	41.83	47.68	43.27	39.41
25	30.07	36.71	31.42	27.76
18	15.59	11.75	14.34	16.27
15	17.24	22.32	19.19	16.44
10	17.50	14.45	16.77	18.11
6	12.52	15.81	13.46	12.15