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Segmenting the Wine Market Based on Price: Hedonic Regression when Different Prices mean Different Products

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Abstract

Many economists have estimated hedonic price functions for red and white wine. However, estimating a single hedonic price function imposes the assumption that the implicit prices of the attributes are the same for any red or white wine. We argue that even within these two categories, wines are differentiated, and disregarding this heterogeneity causes an aggregation bias in the estimated implicit prices. By estimating hedonic functions specific to price ranges, we show that the wine market is segmented into several product classes or market segments. We find that a model accounting for the existence of wine classes has greater ability to explain the variability in the data and produces more accurate and interpretable results regarding the implicit prices of the attributes.

Keywords: *Hedonic regression; market segmentation; structural breaks; wine.*

JEL classifications: *L66, Q13.*

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1. Introduction

Numerous authors have estimated hedonic functions for wine. Although part of this body of research focuses attention on a single type of wine such as Bordeaux, many studies estimate hedonic functions broadly applied to either red or white wine and in some cases to both. The implicit assumption in these studies is that the hedonic relationship between prices and attributes is unique and little variation in that hedonic relationship exists between or within the red and white wine classification. Using data on red wine, we investigate the possibilities that multiple wine classes or market segments exist and that separate hedonic functions should be estimated for each wine class.

The article proceeds as follows: first, a brief review of the existing hedonic literature is presented, and the case for the existence of differentiated wine classes is made. Then, the hedonic model is introduced as the theoretical basis of the analysis, the dataset presented and the empirical specification discussed. A methodology to identify market segments is then developed and applied, and class-specific hedonic models are estimated. Finally, the results are presented, and their implications discussed in the light of a comparison between the class-specific (or segmented) modelling approach vs. the traditional pooled approach.

2. Literature Review

The literature seeking to identify the determinants of wine prices using hedonic techniques is well established. A considerable number of studies have been carried out to determine which wine attributes significantly affect wine prices: Combris *et al.* (1997, 2000) showed that when regressing objective and sensory characteristics on wine price, the objective cues (such as expert rating score and vintage) are significant, whereas sensory variables (such as tannin content and other measurable chemicals) are not. Much of the literature (Oczkowski, 1994; Landon and Smith, 1997; Angulo *et al.*, 2000; Schamel and Anderson, 2003) indicates that ratings by specialised magazines are significant and should be included while modelling wine prices. Possible explanations for the insignificance of sensory cues are the difficulty of isolating the effect of each chemical on the final flavour and smell, and that only a small percentage of wine purchasers are connoisseurs. Therefore, expert ratings act as a signal to the consumer. It is uncertain whether expert ratings influence prices because they are good proxies for quality of the wine or because of their marketing effect. Oczkowski (2001) finds that tasting scores are only proxies for quality, and uses two-stage ordinary least squares and factor analysis to correct for measurement error in the independent variables. On the other hand, Schamel and Anderson (2003) find no evidence of such a problem in their sample. The region of production, capturing production cost differentials and the effects of the collective reputation of the district, and the vintage are often reported as significant variables (Angulo *et al.*, 2000; Schamel and Anderson, 2003). Steiner (2004) finds a declining valuation of French wines with geographical appellation in the British market.

3. Market Segmentation

Although various concerns regarding econometric pathologies endemic to the hedonic wine literature appear to be legitimate (see Oczkowski, 2001, regarding measurement error and Unwin, 1999, on heteroskedasticity, collinearity and an extensive critique of the field), we argue that the extreme heterogeneity of wine as a product class is a *prima facie* reason why fundamental model specification issues should be of principal concern to market analysts. Related to this issue, Thrane (2004) pointed out that it is unlikely that the same hedonic function will be applicable for red and white wines. That is, whether wine attributes affect red and white wines in the same way is a matter that should be tested empirically. In our opinion, the question can be posed on *a priori* grounds. For example, as the ageing potential of red and white wines differs considerably, it seems reasonable to expect that the implicit price of ageing will also be distinct.

Although estimating separate hedonic functions for red and white wines appears advisable at a minimum, the approach might not go far enough in reducing sample heterogeneity and may not produce the most meaningful or accurate comparisons of attribute values. The question of how else the market is segmented remains. Consider an example from the real estate literature to illustrate this issue. Researchers routinely estimate separate hedonic functions for single-family houses, duplexes, apartments and commercial buildings. It is recognised that the same attributes (say, squared footage) can affect prices in substantially different ways across property types. On the other hand, these product classes are believed to include properties that are, although heterogeneous, relatively similar. Therefore, consumers see them as variations on the same basic product. However, Straszheim (1974) argued further that market segmentation is present in the housing market even within such categorisations. He showed that by estimating separate hedonic price functions for different geographic areas of the San Francisco Bay area, the sum of squared errors (SSE) in predicting prices across the entire sample were significantly reduced. Freeman (1993) analysed the conditions under which undifferentiated products are traded in segmented markets.

The objective of this study was to investigate whether the wine market should be segmented into differentiated markets or product classes. A major empirical challenge is the identification of such classes, as there are many possible ways to segment the wine market. Both the wine industry (Ernst and Young Entrepreneurs, 1999) and typical wine consumers (Hall *et al.*, 2001) use price categories to define product-class categories, which provides a rationale for one approach to identifying product classes: segment the wine market by price. The market analysis by Ernst and Young Entrepreneurs (1999), which aimed at providing tailored marketing strategies for the Australian wine industry, divided wines into commercial, semi-premium, premium and ultra-premium categories on the basis of retail price ranges[2] and analysed each category. The wine industry tends to self-select into product-class categories. Scott Morton and Podolny (2002) analysed the motivations of California winery owners and their effects on price and quality. They found that the owners who derive strong non-financial returns charge more for their product and placed themselves on the high-quality end of the spectrum. The owners whose focus was mostly financial were less likely to produce high-quality wines.

[2] The authors specify that the price ranges for commercial, semi-premium, premium and ultra-premium are, respectively: less than A$8 or A$10, between A$10 and A$15 or A$20, between A$20 and A$30 or A$50, and more than A$30 or A$50.

On the consumer side, Hall *et al.* (2001) found that price is used as a quality cue and that consumers look for different attributes, or value the same attributes differently, depending on the occasion the wine is meant to be consumed. One could argue that most consumers have a price range in mind before purchase, which depends on the occasion of consumption, and also look for different attributes depending on the occasion: a wine that works well enough for a casual dinner with friends might not be perceived as appropriate for a gala anniversary celebration. In other words, not all wines are fungible across occasions of consumption, and when deciding which wine to buy, the typical consumer compares alternatives within the chosen price range. Consequently, the same attributes can have different relevance across price categories and therefore different estimated coefficients.

Following the Ernst and Young Entrepreneurs (1999) analysis, we assume that four market segments are also applicable to the US red wine market but leave the identification of the classes' boundaries to empirical estimation. Hedonic regressions specific to each wine class are then estimated. Although the literature on wine valuation is extensive, to our knowledge, segmentation of the US red wine market has not been investigated and an analysis of the potentially different effects of product attributes across price segments has not been accomplished.

4. Theoretical Context

Following the standard hedonic price model (Rosen, 1974), the price of wine, P, is assumed to be described by a hedonic price function, $P = P(z)$, where z is a vector of attributes. The hedonic price of an additional unit of a particular attribute is determined as the partial derivative of the hedonic price function with respect to that particular attribute. Each consumer chooses an optimal bundle of attributes and all other goods in order to maximise utility subject to a budget constraint. For continuously varying attributes, the chosen bundle will place the consumer so that his or her indifference curve is tangent to the price gradient, $\partial P/\partial z_j$, for each attribute. Therefore, the marginal willingness to pay for a change in a wine attribute is equal to the derivative of the hedonic price function with respect to that attribute. Finite differences $\Delta P/\Delta z_j$ represent marginal willingness to pay for discretely varying attributes. Given that the market is segmented by price categories, the hedonic analysis is then represented by a set of hedonic price functions of the general form $P = P_m(Z)$ for $P \in (\ell_m, h_m]$, $m = 1,\ldots, s$, where s denotes the number of segments, and ℓ_m and h_m the lower and upper price boundaries of market segment m, respectively, with corresponding marginal willingness to pay for attributes given by $\partial P_m/\partial z_j$ or $\Delta P_m/\Delta Z_j$ for market segment m.

5. Data

The dataset is composed of 13,024 observations derived from 10 years (1991–2000) of ratings scores reported in the *Wine Spectator* magazine (online version) for California and Washington red wines. Four of the variables are non-binary: (i) price of the wine adjusted to 2000 values by a consumer price index (CPI) for alcohol, (ii) score obtained in expert sensory evaluation by the *Wine Spectator*'s experts, (iii) the number of cases produced and (iv) the years of ageing before commercialisation. Descriptive statistics for these variables are reported in Table 1. Note that

Table 1
Descriptive statistics of quantitative explanatory variables

State	Variable	Mean	Median	Minimum	Maximum
California*	Price‡	31.1	22	3	2,000
	Cases	6,719	1,467	16	950,000
	Score	86.1	87	60	99
	Age	2.8	3	1	9
Washington†	Price‡	23.3	20	5	144
	Cases	6,720	1,000	45	550,000
	Score	86.8	87	67	96
	Age	2.8	3	1	7

Notes: *11,774 observations.
†1,250 observations.
‡Adjusted to year 2000 by a CPI index for alcohol.

wine prices have a positively skewed distribution, but the majority of the observations fall in the \$10 to \$50 range. California has more wines in the 'expensive' category than Washington, with few Washington wines exceeding \$100.

Indicator variables were used to denote regions of production, wine varieties and the presence of label information. The regions of production for California wines include Napa Valley, Bay Area, Sonoma, South Coast, Carneros, Sierra-Foothills and Mendocino, while Washington wines were not separated by regions. These geographical partitions are those adopted by the *Wine Spectator* to categorise the wines, often pooling several American Viticultural Areas (AVAs) in the same region. Varieties include Zinfandel, Pinot Noir, Cabernet Sauvignon, Merlot and Syrah grapes, as well as wines made from blending of different varieties (non-varietals). The vintage year is available for each wine along with other label information such as 'reserve' and 'estate produced'. Table 2 reports all variables and abbreviations used throughout the paper together with a brief description.

6. Specification

Economic theory often suggests the expected sign of the partial derivatives of price with respect to specific attributes but does not restrict functional form. Nevertheless, the choice of the functional form of the hedonic model is fundamental because it determines how the marginal prices will be functionally related to the attributes. Triplett (2004) argued that model specification is ultimately an empirical matter. Given the uncertainty surrounding the correct specification, a flexible functional form is arguably a prudent empirical modelling strategy. A series of possible transformations of the dependent variable were considered and evaluated on the basis of variance stabilisation, normality of the residuals and misspecification.[3] As in Landon and Smith (1997), we find that the inverse square root is the best performing transformation. The final specification of the

[3] The Goldfeldt–Quandt test was used to detect heteroskedasticity proportional to predicted values and the RESET test for misspecification. For the normality of the residuals, we employed three different tests: Anderson–Darling, Kolmogorov–Smirnoff and Ryan–Joiner.

Table 2
Descriptions of the abbreviations used for the explanatory variables

Predictor	Short description
Score	Rating score from the *Wine Spectator*
Scscore	Score centred by subtracting its mean
Scscore2	Scscore squared
Age	Years of ageing before commercialisation
Agesc	Age centred by subtracting its mean
Agesc2	Agesc squared
Cases	Number of cases produced
Lncas	Natural log of hundreds of cases produced
Napa	Region of production
Bay Area	
Sonoma	
South Coast	
Carneros	
Sierra Foothills	
Mendocino	
Washington	
Non-varietal	Grape variety
Pinot Noir	
Cabernet	
Merlot	
Syrah	
Reserve	'Reserve' was reported on the label
Vineyard	Specific name of the vineyard on the label
Estate	'Estate' produced wine
91, …, 99	Vintage
Wa	Washington State wines

independent variables was also determined by screening possible transformations of the non-binary variables and examining excluded variable residual plots. Furthermore, intercept and slope shifters are used to allow separate regression functions for Washington and California wines. The functional form ultimately selected is the following:

$$\begin{aligned}
\text{Price}^{-0.5} = {} & \beta_0 + \beta_0^w + (\beta_1 + \beta_1^w \text{WA})(\text{Score}) + (\beta_2 + \beta_2^w \text{WA})(\text{Score})^2 \\
& + (\beta_3 + \beta_3^w \text{WA})(\text{Age}) + (\beta_4 + \beta_4^w \text{WA})(\text{Age})^2 \\
& + (\beta_5 + \beta_5^w \text{WA})\ln(\text{Cases}) + \sum_{i=1}^{5} (\beta_{5+i} + \beta_{5+i}^w \text{WA})(\text{Variety}_i) \\
& + \sum_{i=1}^{9} (\beta_{10+i} + \beta_{10+i}^w \text{WA})(\text{Vintage}_i) \\
& + \sum_{i=1}^{3} (\beta_{19+i} + \beta_{19+i}^w \text{WA})(\text{Label}_i) + \sum_{i=1}^{7} \beta_{22+i}(\text{Region}_i) + \varepsilon_i
\end{aligned} \tag{1}$$

where WA denotes an indicator variable for Washington State.

The model in equation (1) was estimated using ordinary least square (OLS). Formal testing detected a moderate degree of heteroskedasticity,[4] but the possible gains in estimation efficiency that might be achieved by adjusting the estimator for an appropriate heteroskedastic process were muted by the consistency of the OLS estimator and the large sample size on which the estimates are based.[5] Nevertheless, as a matter of caution the covariance matrix of the parameters was estimated using White's consistent heteroskedasticity-robust estimator.

7. Structural Breaks in Prices

Conceptually, the problem of partitioning the data by price is one of locating a set of n breakpoints that represent the price ranges that demarcate $n + 1$ market segments. We assume that four differentiated market segments exist, thereby setting the number of structural breaks, n, to three. To estimate the optimal location of the structural breaks, the criterion of maximising goodness of fit to the data was adopted. In particular, the set of breakpoints were chosen that minimised the SSE across the four models (one for each price segment) over all the possible different market partitions. The combinatorial nature of the search problem is clear: the number of alternative possible market segmentations is large, and for each of them four vectors of OLS coefficients are needed to calculate the test statistics. In order to reduce the number of calculations, 36 possible breakpoints located over the range from \$10 to \$70 were set. The grid commenced with increments of \$1 in the lower range of prices, from \$10 to \$35, where most of the data lie; then with steps of \$2 in the range from \$35 to \$45, but \$40 was also included; and finally with steps of \$5 from \$45 to \$70. An algorithm was written in GAUSS to estimate the statistics for all combinations of three breakpoints yielding calculable parameter estimates (i.e. for non-singular explanatory variable matrices). Once the optimal price breakpoints were located, price range-specific hedonic regressions were estimated using OLS.

8. Results and Discussion

The price breakpoints minimising the SSE identified four price categories corresponding to the four hypothesised market segments: commercial wines (price less than \$13), semi-premium (between \$13 and \$21), premium (between \$21 and \$40) and ultra-premium ($\geqslant$\$40).[6] The sample sizes associated with these market segments are 1,635, 4,114, 4,809 and 2,475 observations, respectively.

Estimated coefficients of model (1) for the pooled (estimating a single hedonic function) and the segmented models are reported in Tables 3 and 4. Coefficients

[4] It should be noticed that the power of a test increases as the sample size grows larger. In the limit, if the sample is large enough, a formal test will reject virtually *any* hypothesis stated in the form of strict equality.

[5] There is also the mitigating issue of the need to discover the correct heteroskedastic structure of the error process.

[6] A reasonable concern is that the price breakpoints might not be the same for California and Washington. To investigate this hypothesis, we run the GAUSS algorithm on the two separated datasets. Interestingly, we find that the price categories minimising SSE are the same for WA, CA and the pooled dataset.

Table 3

Ordinary least square estimates for pooled and segmented hedonic functions (first set)

	Pooled	Segmented			
Adjusted R^2	0.67	0.91*			
		Commercial	Semi-premium	Premium	Ultra-premium
		0.29	0.21	0.19	0.33
No.	13,024	1,635	4,114	4,809	2,475
Covariate	Coefficient × 10^2 (t-ratio)				
Constant	21.999	29.233	23.943	18.794	14.543
	(104.7)	(56.66)	(140.3)	(116.6)	(50.2)
Scscore	−0.620	−0.275	−0.158	−0.145	−0.168
	(−61.29)	(−6.36)	(−15.86)	(−18.69)	(−10.79)
Scscore2	−0.022	−0.005	−0.008	−0.007	−0.027
	(−16.47)	(−1.25)	(−6.61)	(−6.01)	(−10.35)
Agesc	−1.302	−0.572	−0.185	−0.185	−0.175
	(−23.69)	(−4.62)	(−4.62)	(−4.5)	(−1.83)
Agesc2	0.108	0.334	0.078	0.038	−0.109
	(2.63)	(2.71)	(2.06)	(1.24)	(−2.01)
Lncas	1.004	0.486	0.292	0.290	0.185
	(41.75)	(7.82)	(15.82)	(16.28)	(5.51)
Napa†	−5.483	−1.602	−1.406	−0.478	0.188
	(−36.77)	(−5.78)	(−13.64)	(−3.51)	(0.83)
Bay Area†	−3.437	−1.266	−0.746	−0.135	0.364
	(−17.34)	(−3.67)	(−5.47)	(−0.84)	(1.41)
Sonoma†	−4.053	−2.251	−1.034	−0.110	0.573
	(−28.31)	(−10.38)	(−11.18)	(−0.82)	(2.55)
South Coast†	−3.222	−2.491	−0.809	0.147	1.246
	(−20.46)	(−8.81)	(−7.47)	(1.02)	(4.89)
Carneros†	−4.291	−2.899	−1.537	−0.086	0.423
	(−23.74)	(−6.28)	(−11.76)	(−0.56)	(1.69)
Sierra Foothills†	−2.327	−1.634	−0.296	−0.037	1.440
	(−10.3)	(−5.26)	(−2.02)	(−0.18)	(4.61)
Mendocino†	−2.406	−1.555	−0.538	0.196	1.183
	(−12.64)	(−5.24)	(−4.22)	(1.18)	(3.91)
Wa†	−0.652	1.178	−0.904	1.001	1.817
	(−0.95)	(1.44)	(−1.38)	(3.91)	(3.74)

Notes: *Calculated stacking the segmented datasets in a single (block diagonal) design matrix and estimating the segmented hedonic model all at once, with a single constant.
†Omitted variable: generic California.

relative to the Washington slope shifters were mostly insignificant in the segmented model and are not included in the tables. Comparing the pooled to the segmented approach, the value of adjusted R^2 increases from 0.67 to 0.91. As in Straszheim (1974), the greater flexibility of the segmented approach allows us to capture the specifics of each wine class, resulting in substantially greater explanatory power.

The hypothesis that OLS regression coefficients are equal across the price categories was tested via a Wald statistic. The test statistic was framed analogous to a Chow-type test, whereby parameters associated with like variables across each of

Table 4
Ordinary least square estimates for pooled and segmented hedonic functions (second set)

	Pooled	Segmented			
		Commercial	Semi-premium	Premium	Ultra-premium
Covariate	Coefficient × 10^2 (*t*-ratio)				
Nonvarietal*	−4.319	−0.910	−0.926	−1.207	−2.096
	(−27.29)	(−1.98)	(−5.93)	(−10.82)	(−9.05)
Pinot Noir*	−3.252	−0.588	−0.727	−1.122	−0.839
	(−32.16)	(−2.04)	(−9.13)	(−15.68)	(−4.01)
Cabernet*	−2.479	−0.684	−0.512	−1.060	−1.333
	(−24.4)	(−3.3)	(−6.7)	(−13.34)	(−6.33)
Merlot*	−2.200	−1.069	−0.759	−0.770	−0.653
	(−21.79)	(−4.77)	(−10.06)	(−9.751)	(−2.95)
Syrah*	−0.582	0.003	−0.392	−0.186	−0.029
	(−4.26)	(0.01)	(−3.8)	(−1.932)	(−0.11)
Reserve†	−1.105	0.690	−0.143	−0.512	0.438
	(−10.89)	(2.36)	(−1.5)	(−7.56)	(4.30)
Vineyard†	−0.858	−1.407	−0.151	−0.281	−0.171
	(−11.46)	(−5.99)	(−2.14)	(−5.25)	(−1.77)
Estate†	−0.601	−2.483	0.171	−0.261	−0.022
	(−2.88)	(−4.72)	(1.01)	(−1.62)	(−0.1)
91‡	5.353	1.590	1.195	1.231	–
	(31.78)	(3.57)	(8.2)	(9.27)	–
92‡	5.339	1.977	1.236	1.190	−0.021
	(31.38)	(4.37)	(8.6)	(9.38)	(−0.06)
93‡	4.372	1.679	1.096	1.156	0.307
	(27.24)	(3.62)	(7.61)	(9.84)	(1.13)
94‡	4.097	0.915	0.824	1.176	0.498
	(27.8)	(2.01)	(5.82)	(10.82)	(2.23)
95‡	3.311	0.333	0.477	0.926	0.657
	(23.24)	(0.75)	(3.41)	(9.00)	(3.48)
96‡	2.397	−0.001	0.236	0.699	0.646
	(17.75)	(−0.003)	(1.7)	(7.06)	(3.52)
97‡	1.749	−0.209	0.225	0.696	0.383
	(13.07)	(−0.45)	(1.58)	(7.3)	(2.38)
98‡	0.393	0.090	0.171	0.408	−0.385
	(2.77)	(0.181)	(1.12)	(4.03)	(−2.4)
99‡	0.668	−0.346	0.170	0.294	0.050
	(5.02)	(−0.72)	(1.1)	(3.08)	(0.34)

Notes: *Omitted variable: Zinfandel.
†Omitted variable: no additional label information.
‡Omitted variable: year 2000.
–,Variable not present in market segment.

the price-segmented models were hypothesised to be equal. White's heteroskedasticity robust estimator was used in the test to represent the covariance matrix of the parameter estimates, and a value of the Wald statistic was then calculated to test the equality of all coefficients across classes. All test results strongly reject the null hypothesis (see Table 5).

Table 5
Wald statistics (*P*-values) testing the hypothesis of parameters' equality across market segment

	Semi-premium	Premium	Ultra-premium
Commercial	7,866	19,112	11,118
	(0.000)	(0.000)	(0.000)
Semi-premium		15,702	20,600
		(0.000)	(0.000)
Premium			9,838
			(0.000)

In interpreting the results in Tables 3 and 4, it is important to note that because of the transformation of the dependent variable, coefficients with a negative sign signify a positive impact of the wine attribute on price, and vice versa. Empirical results conformed to *a priori* expectations: for all estimated models, price increases in ageing and rating score over the range of the data and decreases in the number of cases produced. Confirming previously published results, regional appellations command price premia relative to a generic California wine, with 'Napa Valley' bringing the largest premium. The coefficients associated with the variety variables capture the difference in price relative to Zinfandel grapes and the coefficients for vintages refer to price differences relative to the excluded year 2000. Interestingly, all price impacts are negative and show a very clear pattern: the 1991 and 1992 vintages were the largest in magnitude, and then slowly decreased year by year. This suggests that these indicator variables may not only be representing a vintage effect (e.g. good or bad climatic conditions that can affect wine production) but may also be confounded by a temporal trend of the prices not accounted for by the CPI scaling.[7]

Examination of additional estimated hedonic function coefficients and corresponding implicit prices serves to further characterise each wine class and provide for a further contrast between the approach we propose in this paper and the traditional pooled approach. We emphasise that, because of the transformation of the dependent variable, implicit prices are functions of both estimated coefficients and prices. Average implicit prices for each of the attributes were calculated using market segment-specific price averages and results and figures refer to the appropriate ranges of the data.[8]

The derivative of price with respect to the number of cases produced is strictly negative for all market segments and approaches zero as the number of cases increases. As for the quantitative difference across market segments, increasing total

[7] Several authors (Pakes, 2003; Triplett, 2004) suggested the use of hedonic models to calculate CPI indexes as an alternative to the currently used matched models. The model specification of this research fits the 'time dummy variable' method described by Triplett (2004, p. 48) to calculate CPI indexes. The fact that a time trend is still present despite the fact that prices had already been CPI-adjusted suggests that, as many authors observed, the two methods yield considerably different results.

[8] We limit the number of figures presented in this article. Remaining figures and tables are available from the authors upon request. For the sake of reproducibility, the average prices relative to each market segment (commercial, semi-premium, premium and ultra-premium) are \$10.01, \$17.11, \$28.38 and \$73.90, respectively.

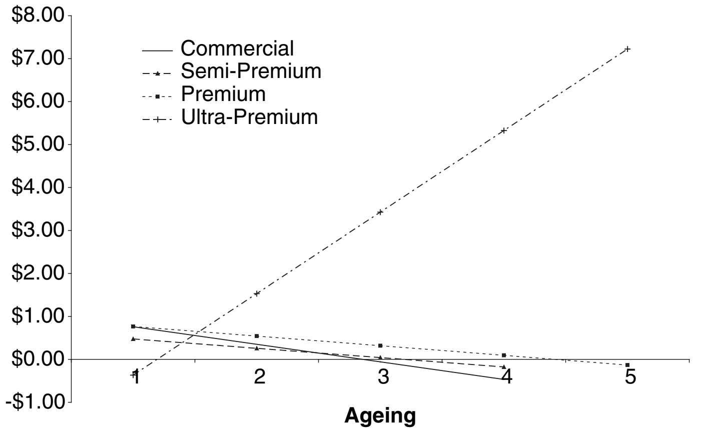

Figure 1. Implicit price of ageing for commercial, semi-premium, premium and ultra-premium wines; calculated using estimates from the segmented model and class-specific price averages

production decreases the market price of wines only slightly in the commercial market segment. The decrease is more pronounced in the two middle segments and is quite substantial in the ultra-premium wine segment (more than five times the estimate relative to the commercial segment). By estimating separated models, we are able to segregate wines that have a 'collectible' or 'cult wine' value from the 'consumption'-type wines. The value of an additional point in the *Wine Spectator* tasting score shows an analogous effect: better scores in the tasting review increase the price of the wine significantly. This effect is increasingly important in order of the commercial, to semi-premium and premium market segments, and becomes highly relevant for the ultra-premium wines.

Differences across market segments regarding the impact of cellaring on wine price are even more pronounced (Figure 1). As expected, wine ageing for the commercial, semi-premium and premium classes exhibits decreasing marginal returns over time. In contrast, ultra-premium wines show different pricing dynamics: the implicit price of ageing increases over the full range of the data. The pooled regression approach does not account for qualitative differences (different signs or slopes across price segments), as only one coefficient (or, for the case of polynomials, one set) is estimated for each attribute. On the other hand, marginal prices are weighted by price, so that quantitative differences are embedded in the regression even in the pooled approach.

Examples of wine class-specific peculiarities in the estimated implicit prices are multiple. Washington wines sell for a discount in the premium and ultra-premium classes, but are no different from California wines in the commercial and semi-premium markets. Blended wines sell for a high premium in the fine wines segment, while they are not different from Zinfandel wines in the inexpensive price segment.[9]

[9] Blended wines are a heterogeneous category. They range from 'table wines' made from several grape varieties mixed in unknown percentages to high-quality, finely balanced wines, such as Meritage. In this instance, the segmented approach allows differentiating between these attributes that share a common denomination, but are inherently different.

Among the varietals, Merlots have the highest associated price premium in the commercial segment, while Cabernets and Pinot Noirs are the most expensive ultra-premium varietal wines. In general, we find that the segmented model produces a much richer and detailed amount of information relating to the character of wine markets.

Finally, we emphasise that estimated price premia from the pooled approach are consistently higher than those from the segmented approach. This can be explained in the context of the different interpretation of the estimates: the price premia associated with the pooled data refer to the mean value of the excluded variable for the *entire* price range, while the segmented price premia refer to the mean value of the excluded variable *within* the price category. The difference is not merely semantic. If wines in different classes are actually different products, this effect can result in false significance of the explanatory variables.

9. Conclusions

We provide empirical evidence that the wine market is differentiated into multiple segments or wine classes. We find that a model considering market segmentation has greater ability to explain the variability of the data and, just as importantly, produces more defensible and informative estimates of the hedonic relationship between prices and wine attributes. The analysis identifies wine classes based on price ranges as well as out-of-sample information relating to the existence of different wine segments. By specifying hedonic functions for different product-class categories, we find evidence that consumers value the same wine attributes differently across categories.

There are many possible ways to segment the wine market. Although the current approach produced reasonable results, the matter of how best to identify segments in the wine market remains an open question. Research is on-going to develop methods that identify wine classes using information in addition to price and that endogenously determine the number of price segments.

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