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

Marco Costanigro, Jill J. McCluskey and Ron C. Mittelhammer

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*Costanigro: Ph.D. candidate, School of Economic Sciences, Washington State University; McCluskey (corresponding author): Associate Professor, School of Economic Sciences, Washington State University; Mittelhammer: Regents Professor, School of Economic Sciences and Department of Statistics, Washington State University, Pullman, WA; The authors with to thank without implicating Jon Yoder for helpful discussion.

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Abstract

It can be argued that the price of wine embodies characteristics that differentiate the product. It follows that many consumers use price as a signal of quality. Many economists have estimated hedonic price functions for wine. However, estimating a single hedonic price function imposes the assumption that the implicit prices of each attribute are the same across price categories. The objective of this paper is to determine appropriate structural breakpoints in wine prices that segment the market into prices categories and test whether the impact of specific wine attributes on price are different across price categories. We confirm that implicit prices for attributes differ across these price categories. We conclude that at least two different wine classes exist: "consumption wines" and "collectible wines." We argue that these classes identify separate products that fulfill different needs and should be considered separately.

Key Words: Hedonic regression, wine, price segmentation, structural breaks

Introduction

A basic question often left in the background in the wine economics literature is how consumers actually select the wines they purchase. In the marketing literature, Spawton (1991) identifies four different categories of wine consumers: connoisseurs, aspirational drinkers, beverage wine consumers and new wine drinkers. Each buyer type has different attitudes towards wine and different preferences. For all types, the main factors influencing the purchasing decision are previous experience and knowledge of the product, objective cues such as production region, brand, and label, the occasion in which the wine will be consumed, and the price itself. Since the quality of a wine cannot be assessed until the moment of consumption, there is an element of risk in wine purchasing, and producers are induced to signal quality to consumers. Pricing, collective reputation associated with the production region, and brand names are examples of how wineries can influence purchasing decisions.

Wine is a classic example of an experience good, because its quality cannot be evaluated before consumption. Even in the case in which the consumer knows a particular wine and winery, the possibility of a "corky" bottle cannot be excluded. Therefore, there is always an element of risk in buying wine. However, risk is lower for inexpensive, low-quality wine, higher for the middle-priced bottles, and again lower for the high-priced fine wine bottles for connoisseurs. The argument is that perceived risk increases as economic investment increases (the price of the bottle) but decreases as information available before purchase increases. For inexpensive wines, perceived risk will be limited, since consumers have little to lose. On the high end of the price range, connoisseurs who buy expensive wines usually know the wineries they are purchasing from, and further most wines are reviewed or publicized in specialized magazines. For the non-connoisseurs, "important" wines can be purchased in specialty shops and wine stores, where they will find knowledgeable personnel who can advise them on quality. The middle price range is the most risky because the consumer faces a large number of different wines and wineries, mostly unknown to the buyer, displayed side by side on the grocery store shelf. Therefore, it seems reasonable to hypothesize that information about the marginal value of the objective attributes could be more useful in the middle-price category, where consumers have relatively less information to facilitate choice among a wide array of different wines.

Wine consumption is often associated with social occasions. Thus the choice of the right wine for the occasion becomes frequently a vehicle of self-representation and can drive the final selection. This aspect makes wine a very complex and interesting product to study. Marketing research (Hall *et al*., 2001) confirms that consumers look for different attributes, or value the same attributes differently, depending on the occasion in which the wine is meant to be consumed. While obtaining data for each different occasion is quite difficult, it seems reasonable that different occasion of consumption are associated with different price ranges. Hall *et al* (2001) finds that price is used as a quality cue.

Following this line of reasoning, we hypothesize that most consumers have a price range in mind before purchase, which depends on the occasion of consumption. Once at the store, unless the consumer has a particular wine and winery in mind, he or she compares possible alternatives within the chosen price range. The objective of this paper is to determine appropriate structural breakpoints in wine prices that segment the market into prices categories and test whether the impact of specific wine attributes on price are different across price categories. We accomplish the latter objective with hedonic regression, which has been utilized extensively in wine studies.[1]

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[1] Several authors have utilized the hedonic approach in investigating the determinants of wine prices. Determining which attributes are good candidates as explanatory variables is a fundamental question which is often constrained

The principle underlying hedonic regression is straightforward: the price of a good is a function of the quality attributes the good contains (Rosen, 1974). Goods containing higher levels of quality attributes, *ceteris paribus*, will obtain a price premium on the market. By regressing price on the attributes, the hedonic functions provide estimates of the influence of each attribute on the equilibrium price, embedding both supply and demand factors, costs and willingness to pay (Nerlove, 1995).

Straszheim (1974) first argued that it is appropriate to segment markets for purposes of hedonic price estimation, his application being an analysis of property values. He showed that by estimating separate hedonic price functions for different geographic areas of the San Francisco Bay area, the significantly reduced the sum of squared errors in predicting prices across the entire sample. Also in the context of property values, Freeman (1993) made the case that two conditions must be met to for different hedonic price functions to exist: 1) either the structure of demand, the structure of supply, or both, must be different across segments; and 2) purchasers in one segment must not participate significantly in other segments. There must be some barrier that prevents arbitrage in response to differences in implicit prices. We argue that both of Freeman's conditions are met for wine. First, supply differs across segments because of limited land in the highest reputation locations such as Napa Valley and differing land values across growing regions. Based on the arguments noted earlier regarding the intended occasion of

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by the available data. Combris *et al*. (1997, 2000) showed that when regressing objective characteristics and sensory characteristics on wine price, the objective cues (such as expert score and vintage) are significant, while sensory variables such as tannins content and other measurable chemicals are not. Nevertheless, most of the literature (Oczkowski 1994; Landon and Smith 1997; Shamel *et al*. 2003, Angulo *et al*. 2000) indicates that ratings by specialized magazines are significant and should be included in modeling wine prices. Possible explanations for the insignificance of sensory cues are the difficulty of isolating the effect of each chemical on the final flavor 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. In addition to expert ratings, the region of production, capturing 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).

consumption, demand differs across segments also. On Freeman's second condition, fine wines are typically sold in wine stores or at wineries and not in grocery stores, where more inexpensive wines are sold.

Although the literature on wine valuation is extensive, to our knowledge, segmentation of the wine market by price has not been investigated and an analysis of the potentially different effects of product attributes across price segments has not been accomplished. The analysis in this article proceeds in the following way: the hedonic model is briefly introduced as the theoretical basis of the analysis, then the data set is discussed, the empirical specification and price-breakpoints identifying different price segments are presented, the estimation results are discussed, and conclusions are offered.

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 maximize 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 representable in terms of a set of hedonic price functions in 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 denote 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.

Data

The data set is composed of 13,157 observations derived from ten years (1991-2000) of tasting ratings reported in the *Wine Spectator* Magazine (online version) for California (11,869 observations) and Washington (1,288 observations) red wines. Four of the variables are non-binary: price of the wine adjusted to 2000 values by a consumer price index (CPI) for alcohol, score obtained in the expert sensory evaluation provided by the *Wine Spectator*, the number of cases produced, and the years of aging before commercialization. Descriptive statistics for these variables are reported in Table 1. Note that wine prices have a 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 very 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 the ones adopted by the *Wine Spectator* to categorize the wines, often pooling several American Viticultural Areas (AVAs) in the same region. Varieties include Zinfandel, Pinot, Cabernet, Merlot and Syrah grapes, as well as wines made from blending of different varieties (non-varietal). 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 short descriptions.

Specification

Economic theory generally suggests the 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 is fundamental since it determines how the marginal prices will be calculated. Given the uncertainty about the correct functional specification, a flexible functional form is desirable. Heteroskedasticity and multicollinearity are common issues in hedonic models and should be addressed when choosing a specification. The large majority of applications in the hedonic literature apply ordinary least squares (OLS) to a log-linear specification apparently to achieve a better fit and for the variance stabilizing properties of the log transformation.

In our study, ten different transformations of the dependent variable were considered: a grid search involving 8 discrete choice of the dependent variable in the form $(Price)^{\alpha}$ where α varied from –2 to +2 with a step of 0.5 and with $\alpha = 0$ eliminated, the natural log transformation, and the general Box-Cox transformation. For screening of functional forms, the right-hand side was over-parameterized to allow for greater flexibility. The four non-binary variables each appeared in third-order polynomial form, and the explanatory variable specification was completed by including the full set of indicator variables for region, vintage and label indication. In addition, intercept and slope shifters were used to initially allow for completely separate regression functions for Washington and California wines, which almost doubled the number of estimated parameters (the Washington observations did not incorporate a regional or appellation effect). To mitigate induced multicollinearity, the explanatory variables appearing in polynomial form were centered by subtracting their mean.

The resulting models were estimated via OLS and compared through evaluation of several statistics including the following: goodness of fit was assessed through F-test for overall significance of the regression as well as via the adjusted R^2 statistic; heteroskedasticity proportional to the predicted values was tested via Goldfeld-Quandt statistics; Ramsey's RESET test was used to detect misspecification; and finally the normality of the residuals was checked with three different statistical tests (see Table 3).

Interestingly, both the Box-Cox transformation (with $\lambda = -0.36$) and the negative square root transformation outperformed the widely used natural-log transformation in all the performed tests. Even though a formal likelihood ratio test rejected the hypothesis that the negative square root and Box-Cox transformations were statistically the same (H_o:$\lambda = -0.36$ versus H_a:$\lambda = -0.50$), the two models yielded very similar results in statistical tests as well as in model implications. The negative square root transformation $(\text{price})^{-0.5}$ was chosen on the basis of its generally better (albeit marginally) fit and statistical test results in comparison to competing functional specifications.

The analysis then proceeded to a more parsimonious specification of the regressors: a joint F-test suggested dropping the third power for the variables *Age* and *Score*, while *Cases* was highly significant through the third power. Examination of excluded variable residual plots with LOWESS nonparametric fit superimposed confirmed that the relationships between *Price* and *Age* and between *Price* and *Scor*e was well approximated by a quadratic form. The third-order polynomial of *Cases* was highly influenced by outliers, resulting in indefensible patterns that substantially deviated from the nonparametric fit (Figures 1 and 2). In addition, the polynomial form of *Cases* induced a large amount of collinearity in the estimated equation (with variance inflation factors of 7.6, 45.2 and 25.8, respectively, for the polynomical terms).

The nonlinear relationship between *Price* and *Cases* was further investigated and a linearizing transformation considered. A grid search was performed in the form $(Cases)^{\alpha}$, with α varying from –2 to +2 with a step of 0.5 and $\alpha = 0$ excluded, plus the natural log transformation. Each of the transformed variables was then plotted against residuals exluding the effect of Cases, confirming that the natural log transformation was the most appropriate choice for linearizing the relationship (A Box-Tidwell analysis was also performed, which resulted in a transform of $\lambda = .1251$ that was not significantly different from the log transformation) . The functional form for the hedonic function ultimately selected was the following:

$$\begin{aligned} Price^{-0.5} = {} & \left(\beta_1 + \beta_1^w WA\right)(Score) + \left(\beta_2 + \beta_2^w WA\right)(Score)^2 + \left(\beta_3 + \beta_3^w WA\right)(Age) + \left(\beta_4 + \beta_4^w WA\right)(Age)^2 \\ & + \left(\beta_5 + \beta_5^w WA\right) LN(Cases) + \sum_{i=1}^{5}\left(\beta_{5+i} + \beta_{5+i}^w WA\right)(Variety_i) + \sum_{i=1}^{9}\left(\beta_{10+i} + \beta_{10+i}^w WA\right)(Vintage_i) \\ & + \sum_{i=1}^{3}\left(\beta_{19+i} + \beta_{19+i}^w WA\right)(Label_i) + \sum_{i=1}^{7}\beta_{22+i}(Region_i) + \varepsilon_i \end{aligned} \tag{1}$$

The model was then estimated via OLS. As shown in Table 4, formal tests still detected pathologies, but overall the error term was closer to normally distributed and the variance was reasonably stabilized. Misspecification was still present and likely a result of omitted variable bias, which is a problem endemic to most studies employing observational data. As a measure of caution concerning inferences made from the estimated model, the covariance matrix of the parameters was re-estimated using White’s heteroskedasticity consistent estimator and no significant changes occurred to inferences.

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 resulting in *n* + 1 market segments. However, the number and the location of the breakpoints may not be the same for Washington and California wines, so the two Washington and California data sets were first analyzed separately. Since estimating contemporaneously the number of breakpoints and their location is a complicated task, the number of structural breaks, *n*, was initially set to three, therefore identifying four different price ranges: an inexpensive wine market segment, a low-middle, a high-middle and finally a fine wine segment.

To estimate the optimal location of the structural breaks, the criterion of maximizing goodness of fit to the data was adopted. In particular, the set of breakpoints were chosen that minimized the sum of square errors 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, a total of thirty-six 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 lies; 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. Thus, each difference between breakpoints contained a comparable number of observations.

An algorithm was written in Gauss to calculate the statistics for all combinations of three breakpoints yielding calculable parameter estimates (i.e., for nonsingular explanatory variable matrices). For the California data set, a total of 6,489 combinations were tested. The combination of price breakpoints minimizing the sum of squared errors (SSE) was $13, $21 and $40. The algorithm was then rerun on the pooled California-Washington data set, with the model specified as in equation 1), without any change in the results: optimal breakpoints at $13, $21 and $40. The sample sizes implied were 1,644, 4,148, 4,861 and 2,501 observations for the inexpensive, mid-low, mid-high and fine wines segments, respectively. It is striking that the overall explanatory power of the segmented models is maximized through selecting similar market segmentation for both California and Washington wines. This result accords well with our earlier assumption about consumer behavior: wine shoppers have a price range in mind, and they choose between California and Washington wine based on that price range. We conclude that the same four market segments are appropriate for both California and Washington: inexpensive wines (price less than $13), mid-low (price between $13 and $21), mid-high (price between $21 and $40) and fine wines (Price greater than or equal to $40).

The hypothesis that OLS regression coefficients are equal across these price categories was tested in the full model including both California and Washington wines via a Wald test statistic. The test statistic was framed analogous to a Chow-type test, whereby parameters associated with like variables across the each of the price-segmented models were hypothesized to be equal in the test. Results unambiguously confirm that these markets are inherently different from each other (the Wald statistic is equal to 23,153; and the p-value is equal to 0.000), so that separated hedonic models should be estimated.

Results and Discussion

For the sake of comparison, the estimated coefficients of the model [1] using the entire data are reported in Table 5. The empirical results conformed to *a priori* expectations: over the range of the data price is increasing in aging and rating score and decreasing in number of cases produced. For the indicator variables, negative estimated coefficients represent price premia with respect to the excluded non-appellation wine from California. Confirming previously published results, regional appellations award price premia with respect to a generic California wine, "Napa Valley" being the largest in magnitude.

The coefficients for the varieties represent the difference in mean price with respect to Zinfandel grapes, showing that non-varietal wines are awarded the highest price premia, followed by Pinot Noir, Cabernet, Merlot, and Syrah. Interestingly, most of the information reported on the label is related to positive price differentials; as shown by the signs of the coefficients for "estate-produced," "reserve," and even for wines indicating the specific name of the vineyard on the label. Lastly, the coefficients for the vintages refer to the excluded year 2000. All price impacts are negative and show a very clear pattern: the 1991 and 1992 vintages were the biggest in magnitude and then slowly decreasing year by year. This suggests that these indicator variables are not picking up a vintage effect (e.g. good or bad climatic conditions that can affect wine production) [2] but rather a temporal trend of the prices that was not eliminated by the scaling with the CPI.

[2] This is in contrast with results from Ashenfelter, Ashmore, and Lalonde's (1995) study of Bordeaux wine vintage quality and the weather. However, according to the authors the weather in California is much less variable than in Bordeaux. They write, "In California, a high-pressure weather system settles each summer over the California coast and produces a warm, dry growing season for the grapes planted there. In Bordeaux, this sometimes happens—but usually it does not. Great vintages for Bordeaux wines correspond to the years in which August and September are dry, the growing season is warm, and the previous winter has been wet," (page 11).

Hedonic price functions [1] were then estimated for each of the four identified market segments. A preliminary estimation of the implicit marginal prices of the attributes suggested that the selected functional form was still sensitive to outlying observations. Therefore, an analysis of influential observation was performed using leverage, influence on the estimated regression line (DFFITS) and studentized residuals as detection criteria, eliminating a total of 133 data points. Price breakpoints were then re-estimated using the dataset purged of the influential observations, without significant differences in their optimal location. Tables 6, 7, 8 and 9 report the OLS coefficients estimated without influential observations.

While the SSE minimization criterion partitioned the data set in subsets of irregular sample size, the explanatory power was more evenly distributed across models. The adjusted R^2 was 0.29, 0.21, 0.19 and 0.33 for the four models ranging from inexpensive to fine wines, respectively. This result might at first seem disappointing and inferior to the one obtained earlier using the classical approach of the single regression (adjusted R^2 based on the entire data set was 0.67). However, a straight comparison is inappropriate, since segmenting the data changes the dependent variable and the variability measure of it. To generate a meaningful comparison of explanatory power, the explanatory matrix was re-specified as a block diagonal matrix, where each block contained the regressors relative to the appropriate market segment. The adjusted R^2 corresponding to the prediction of prices across all market segments, and thus based again on the entire data set, was 0.91.

Average 95% confidence intervals for the marginal prices of each of the attributes were calculated using price averages specific to each market segment and then plotted in the range of the data. As Figure 3 shows, the derivative of price with respect to the number of cases is strictly negative for all market segments and asymptotically approaches zero as the number of cases increases. The quantitative difference across market segments is evident: increasing total production decreases only slightly the market price of wines in the inexpensive market segment, the decrease is more pronounced in the two middle segments, and is quite substantial in the fine wine segment. This is not surprising since the highest priced wines often have a “collectible” or “cult wine” value.

The value of an additional point in the *Wine Spectator* tasting score shows an analogous trend (see Figures 4 and 5): better scores in the tasting review increase the price of the wine significantly. This effect is increasingly important starting from the inexpensive, to mid-low and mid-up wines, and becomes extremely relevant for the fine wines. The segment (less than 75) where the derivative of score is negative consists of very few observations. It is almost three standard deviations below the mean.

The effect of the aging on the wine price is more articulated (figure 6). As expected wine aging for the inexpensive, mid-low and mid-high wines shows decreasing marginal returns. Marginal effects become negative after two years of aging for wines in the inexpensive segment, three years for the mid-low and four for the mid-up. In contrast, fine wines show completely different pricing dynamics: the aging function shows increasing marginal returns over the range of the available data (see Figure 7). This behavior can again be explained by the collectible value of fine wines.

In Figure 8, we plot the average price premia for regional appellations (with respect to a non-appellation California wine) for each of the price segments. Estimated price premia range from $0.70 to $1.70 in the inexpensive segment and from $0.40 to $2.10 in the mid-low. Observing the mid-high segment, it is interesting that only Napa Valley obtains a positive price premium. In the fine wines market segment, the regional designations are either insignificant or sell for a discount. A similar trend (see Figure 9) can be identified for the other information reported on the labels (estate produced, reserve and vineyard specific wines), which seems to be somewhat valuable up to the mid-high price segment and is irrelevant for the fine wines.

According to these estimates, it can be seen that Washington state wines still struggle to gain recognition, especially in the mid-high and fine wine market segments. On the other hand, it should be noticed that the indicator variable compares non-appellation Washington wines to non-appellation California wines. Thus, it is still possible that Washington appellations (such as “Columbia Valley”), if introduced in the regression, might actually obtain price premia.

The estimates relative to the average price premia associated with the different varieties are noteworthy. 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. This is the reason for the estimates reported in Figure 10: blended wines sell for a very high premium in the fine wines segment, while they are no different from Zinfandel wines (the excluded category) in the inexpensive price segment. To conclude, estimated coefficients for the vintages still delineate a trend of increasing real prices over time.

These findings corroborate our early assumption that wines in different price categories are actually different products. Differences in estimated coefficients and implied marginal prices of the attributes across price segments are both quantitative and qualitative. Clearly, the pooled regression approach cannot account for qualitative differences (different signs or slopes across price segments), as only one coefficient (or, for the 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.

For a clearer comparison between the two approaches, 95% confidence intervals for the marginal prices of the attributes were recalculated using the OLS coefficients from the pooled regression approach, evaluating them at the same mean prices adopted earlier for the market segments. As expected, the pooled regression restriction of a single coefficient for the whole price range results in apparently biased estimated price premia. This is evident if we compare marginal prices for wine aging calculated using single (see Figure 11) or multiple coefficients (see Figures 6 and 7).

It can be also noticed that estimated price premia from the pooled approach are consistently higher than the ones from the segmented approach. The premia for regional appellation from pooled regression (see Figure 12) are a good example of this effect (compare with Figure 8). This can be explained in the context of the different interpretation of the premia: the price premia associated with the pooled data refer to the mean value of the excluded variable for the *whole* price range, while the segmented price premia refer to the mean value of the excluded variable *within* the price category. The difference is not only semantic. If, as seems to be the case, wines in different price categories are actually different products, this effect will often result in a false significance of the explanatory variables. More importantly, pooled estimation imposes the same restriction on estimated premia, which given our estimated results appear to be incorrect. More importantly, pooled estimation imposes a same-sign restriction on premia estimated across price categories, which given our estimated results appear to be incorrect.

Conclusions

By specifying hedonic functions for different price categories, we find evidence that consumers value the same wine attributes differently across wines, depending on the price range under consideration. Differences across the lower priced segments are mostly relatively small, while the fine wines segment has a radically different hedonic function. Number of cases produced, expert rating scores, and aging have a stronger impact on price in the fine wine price categories than in the lower priced categories. Regional appellations, along with other information reported on the label, have a positive effect on price only for the inexpensive and mid-low price segments, and are nonsignificant or negative for the higher ones. Therefore, at least two substantially different market segments could be identified.

These results corroborate our hypotheses concerning consumer behavior and are meaningfully interpreted at the light of such assumptions. Wine shoppers make purchasing decisions with a price range in their mind. Within the decided-on price range, bottles are compared and a purchasing decision is made. For lower-priced wines, the decision usually takes place at the grocery store, with numerous wines side by side and little information available. In this setting information reported on the label is certainly valuable. Higher price wine shoppers are more wine educated, therefore they value the information from specialized magazines and recognize good wineries. To them, label information adds little or no value to the bottle.

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Table 1. Descriptive Statistics of Quantitative Explanatory Variables

	Variable							
	California				Washington			
	Price*	Cases	Score	Age	Price	Cases	Score	Age
N	11869	11869	11869	11869	1288	1288	1288	1288
Mean	31.06	6719	86.115	2.7646	23.262	6720	86.815	2.8346
St. Dev	51.44	26201	3.955	0.7429	12.523	30764	3.38	0.7714
Median	22	1467	87	3	20	1000	87	3
First Quartile	15	500	84	2	5	377	85	2
Third Quartile	35	6000	88	3	144	2638	89	3
Minimum	3	16	60	1	5	45	67	1
Maximum	2000	950000	99	9	144	550000	96	7

*adjusted by a CPI index for alcohol

Table 2. Descriptions of the Abbreviation Used for the Explanatory Variables

Predictor	Short Description	Predictor	Short Description
Score	Rating Score from the Wine Spectator	WNonvarie	Wa * Nonvarie
Scscore	Score Centered by Subtracting its Mean	Wpinot	Wa * Pinot noir
Scscore2	Scscore Squared	WCabernet	Wa * Cabernet
Age	Years of Aging Before Commercialization	WMerlot	Wa * Merlot
Agesc	Age Centered by Subtracting its Mean	WShyrah	Wa * Shyrah
Agesc2	Agesc Squared	WReserve	Wa * Reserve
Cases	Number of Cases Produced	WVineyard	Wa * Vineyard
Lncas	Natural Log of Hundreds of Cases Produced	WOldvin	Wa * Oldvin
Napa	Region of Production	WEstate	Wa * Estate
bay area		W91	Wa * 91
Sonoma		W92	Wa * 92
South coast		W93	Wa * 93
Carneros		W94	Wa * 94
Sierra foothills		W95	Wa * 95
Mendocino		W96	Wa * 96
Washington		W97	Wa * 97
Nonvarietal	Grape Variety	W98	Wa * 98
Pinot noir		W99	Wa * 99
Cabernet			
Merlot			
Shyrah			
Reserve	"Reserve" was Reported on the Label		
Vineyard	Specific Name of the Vineyard on the Label		
Estate	"Estate" Produced Wine		
91	Vintages		
92			
93			
94			
95			
96			
97			
98			
99			
Predictor	Short Description		
Score	Rating Score from the Wine Spectator		
Wa	Washington State wines		
WScscore	Wa * Scscore		
WScscore2	Wa * Scscore2		
WAge	Wa * Age		
WAgesc	Wa * Agesc		
WAgesc2	Wa * Agesc2		
WCases	Wa * Cases		
Wlncas	Wa * lncas		

Table 3. Test Statistics Result for Several Specification of the Dependent Variable

	Fit		Normality			Specification			Heteroskedasticity
	Adj. R^2.	F	Anderson Darling	Ryian Joiner	Komolgorov Smirnov	Reset (2)	Reset (3)	Reset (4)	Goldfeld Quandt
Transf.			**A-Squared**	**R**	**D**	**F-value**	**F-value**	**F-value**	**GQ**
-2	0.542	260.396	552.548	0.879	0.155	1237.100	692.730	469.090	20.497
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
-1.5	0.605	337.300	295.709	0.938	0.114	713.450	436.320	294.860	9.029
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
-1	0.651	409.242	106.373	0.979	0.066	228.520	172.030	116.840	3.923
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
-0.5	**0.670**	**445.816**	18.584	0.997	0.025	**1.236**	**26.907**	**19.097**	**1.618**
			0.000	0.000	0.000	**0.266**	**0.000**	**0.000**	**0.000**
Box-Cox (- 0.36)	0.669	443.468	**14.972**	**0.997**	**0.023**	9.3751	23.5	***	1.2214
			0.000	**0.000**	**0.000**	0.002	0.000	0.000	0.000
lny	0.644	397.624	62.396	0.974	0.048	187.000	101.960	69.217	1.807
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.5	0.499	219.619	581.245	0.804	0.140	543.330	276.400	184.920	8.911
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
linear	0.211	59.631	2200.000	0.490	0.285	465.850	242.590	168.760	92.490
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
1.5	0.065	16.264	3400.000	0.305	0.385	264.230	147.330	101.640	777.130
			0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.026	6.946	3800.000	0.233	0.421	147.590	82.081	59.130	12204.150
			0.000	0.000	0.000	0.000	0.000	0.000	0.000

NOTE: Probability values are displayed below statistical test values.

Table 4. Test Statistic Results for the Final Specification of the Model

	Fit			Normality			Specification			Heteroskedasticity
	r2 adj	rsqare pred	F	Anderson Darling	Ryian Joiner	Komolgorov Smirnov	Reset (2)	Reset (3)	Reset (4)	Goldfeld Quandt
Transf.				**A-Squared**	**R**	**D**	**F-value**	**F-value**	**F-value**	**GQ**
-0.5	68.50%	68.44%	924.83	19.601	0.9963	0.026	121.36	60.734	40.667	1.496128
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

NOTE: Probability values are displayed below statistical test values.

Table 5. OLS coefficients estimated for the whole range of the data

Name	Estimated Coefficient	St. Err.	T-Value	P-Value
Scscore	-0.006201	0.000101	-61.290	0.000
Scscore2	-0.000221	0.000013	-16.470	0.000
Agesc	-0.013023	0.000550	-23.690	0.000
agesc2	0.001077	0.000408	2.639	0.008
Lncas	0.010043	0.000241	41.750	0.000
Napa	-0.054828	0.001491	-36.770	0.000
Bay Area	-0.034368	0.001982	-17.340	0.000
Sonoma	-0.040526	0.001432	-28.310	0.000
South Coast	-0.032215	0.001575	-20.460	0.000
Carneros	-0.042907	0.001808	-23.740	0.000
Sierra Foothills	-0.023265	0.002259	-10.300	0.000
Mendocino	-0.024064	0.001903	-12.640	0.000
Nonvarietal	-0.043188	0.001582	-27.290	0.000
Pinot Noir	-0.032519	0.001011	-32.160	0.000
Cabernet	-0.024791	0.001016	-24.400	0.000
Merlot	-0.022004	0.001010	-21.790	0.000
Shyrah	-0.005815	0.001363	-4.267	0.000
Reserve	-0.011050	0.001015	-10.890	0.000
Vineyard	-0.008577	0.000748	-11.460	0.000
Estate	-0.006011	0.002084	-2.884	0.004
91	0.053526	0.001684	31.780	0.000
92	0.053393	0.001701	31.380	0.000
93	0.043723	0.001605	27.240	0.000
94	0.040971	0.001474	27.800	0.000
95	0.033106	0.001424	23.240	0.000
96	0.023969	0.001351	17.750	0.000
97	0.017490	0.001338	13.070	0.000
98	0.003927	0.001416	2.774	0.006
99	0.006683	0.001331	5.023	0.000
Wa	-0.006521	0.006865	-0.950	0.342
Wscscore	-0.000670	0.000353	-1.900	0.057
Wscscore2	-0.000229	0.000045	-5.097	0.000
Wagesc	-0.001358	0.001698	-0.800	0.424
Wagesc2	0.003020	0.001327	2.275	0.023
Wlncas	0.002539	0.000648	3.915	0.000
Wnonvarietal	0.021720	0.006681	3.251	0.001
Wpinot	0.031855	0.015590	2.043	0.041
Wcabernet	0.004408	0.006029	0.731	0.465
WMerlot	-0.003268	0.005961	-0.548	0.584
Wshyrah	-0.017619	0.006409	-2.749	0.006
Wreserve	-0.000049	0.003124	-0.016	0.988
Wvineyard	-0.002245	0.002295	-0.978	0.328
Westate	-0.008051	0.006244	-1.290	0.197
W91	-0.025843	0.004982	-5.188	0.000
W92	-0.025630	0.004966	-5.161	0.000
W93	-0.016009	0.004891	-3.273	0.001
W94	-0.023223	0.004730	-4.910	0.000
W95	-0.024038	0.004229	-5.683	0.000
W96	-0.015259	0.004475	-3.410	0.001
W97	-0.007511	0.004306	-1.744	0.081
W98	0.002896	0.004227	0.685	0.493
W99	-0.001246	0.004159	-0.300	0.764
CONSTANT	0.219990	0.002101	104.700	0.000

Table 6. OLS Coefficients for the Inexpensive Price Segment

Name	Estimated Coefficient	St. Err.	T-Value	P-Value
Scscore	-0.002747	0.000432	-6.360	0.000
Scscore2	-0.000050	0.000040	-1.250	0.211
Agesc	-0.005720	0.001236	-4.627	0.000
agesc2	0.003336	0.001229	2.715	0.007
Lncas	0.004864	0.000621	7.828	0.000
Napa	-0.016019	0.002770	-5.783	0.000
Bay Area	-0.012662	0.003450	-3.670	0.000
Sonoma	-0.022510	0.002168	-10.380	0.000
South Coast	-0.024906	0.002825	-8.817	0.000
Carneros	-0.028992	0.004614	-6.284	0.000
Sierra Fthills	-0.016338	0.003101	-5.269	0.000
Mendocino	-0.015547	0.002963	-5.247	0.000
Nonvarietal	-0.009103	0.004589	-1.984	0.047
Pinot Noir	-0.005881	0.002877	-2.044	0.041
Cabernet	-0.006844	0.002068	-3.309	0.001
Merlot	-0.010690	0.002240	-4.772	0.000
Shyrah	0.000034	0.004257	0.008	0.994
Reserve	0.006902	0.002915	2.367	0.018
Vineyard	-0.014065	0.002348	-5.990	0.000
Estate	-0.024832	0.005261	-4.720	0.000
91	0.015896	0.004454	3.569	0.000
92	0.019773	0.004528	4.366	0.000
93	0.016788	0.004639	3.619	0.000
94	0.009151	0.004544	2.014	0.044
95	0.003329	0.004395	0.758	0.449
96	-0.000013	0.004447	-0.003	0.998
97	-0.002087	0.004639	-0.450	0.653
98	0.000904	0.004996	0.181	0.856
99	-0.003464	0.004781	-0.724	0.469
Wa	0.011776	0.008155	1.444	0.149
Wscscore	0.000108	0.000764	0.142	0.887
Wscscore2	-0.000193	0.000104	-1.864	0.062
Wagesc	0.002214	0.002636	0.840	0.401
Wagesc2	-0.003610	0.002231	-1.618	0.106
Wlncas	-0.003175	0.000947	-3.354	0.001
Wnonvarietal	0.012709	0.006106	2.081	0.038
Wpinot	0.014292	0.008504	1.681	0.093
Wcabernet	0.006825	0.005058	1.349	0.177
WMerlot	0.006697	0.004874	1.374	0.170
Wshyrah	-0.009175	0.006759	-1.357	0.175
Wreserve	-0.005386	0.007680	-0.701	0.483
Wvineyard	-0.001409	0.004316	-0.327	0.744
Westate	0.024073	0.007367	3.268	0.001
W91	-0.027969	0.006446	-4.339	0.000
W92	-0.027518	0.006823	-4.033	0.000
W93	-0.016705	0.006956	-2.402	0.016
W94	-0.017803	0.006128	-2.905	0.004
W95	-0.018186	0.007220	-2.519	0.012
W96	-0.015231	0.006209	-2.453	0.014
W97	-0.006280	0.006269	-1.002	0.317
W98	-0.010656	0.006805	-1.566	0.118
W99	0.003889	0.006583	0.591	0.555
CONSTANT	0.292330	0.005160	56.660	0.000

Table 7. OLS Coefficients for the Mid-Low Price Segment

Name	Estimated Coefficient	St. Err.	T-Value	P-Value
Scscore	-0.001581	0.000100	-15.860	0.000
Scscore2	-0.000076	0.000011	-6.615	0.000
Agesc	-0.001850	0.000400	-4.627	0.000
agesc2	0.000782	0.000379	2.060	0.039
Lncas	0.002916	0.000184	15.820	0.000
Napa	-0.014057	0.001030	-13.640	0.000
Bay Area	-0.007460	0.001363	-5.474	0.000
Sonoma	-0.010339	0.000925	-11.180	0.000
South Coast	-0.008094	0.001083	-7.475	0.000
Carneros	-0.015365	0.001307	-11.760	0.000
Sierra Foothills	-0.002957	0.001461	-2.023	0.043
Mendocino	-0.005377	0.001272	-4.228	0.000
Nonvarietal	-0.009262	0.001560	-5.939	0.000
Pinot Noir	-0.007269	0.000796	-9.133	0.000
Cabernet	-0.005120	0.000764	-6.705	0.000
Merlot	-0.007589	0.000754	-10.060	0.000
Shyrah	-0.003915	0.001030	-3.802	0.000
Reserve	-0.001428	0.000951	-1.502	0.133
Vineyard	-0.001513	0.000704	-2.148	0.032
Estate	0.001713	0.001683	1.018	0.309
91	0.011947	0.001457	8.202	0.000
92	0.012360	0.001436	8.606	0.000
93	0.010960	0.001440	7.611	0.000
94	0.008235	0.001415	5.821	0.000
95	0.004769	0.001396	3.416	0.001
96	0.002359	0.001386	1.702	0.089
97	0.002252	0.001421	1.584	0.113
98	0.001711	0.001518	1.127	0.260
99	0.001701	0.001535	1.108	0.268
Wa	-0.009039	0.006515	-1.387	0.165
Wscscore	0.000279	0.000360	0.776	0.438
Wscscore2	0.000018	0.000032	0.568	0.570
Wagesc	-0.001016	0.001306	-0.778	0.437
Wagesc2	-0.002951	0.001154	-2.557	0.011
Wlncas	0.000016	0.000501	0.033	0.974
Wnonvarietal	0.019826	0.006256	3.169	0.002
Wpinot	0.014054	0.006587	2.134	0.033
Wcabernet	0.006774	0.005712	1.186	0.236
WMerlot	0.005231	0.005720	0.914	0.361
Wshyrah	0.006341	0.006161	1.029	0.303
Wreserve	-0.000757	0.003017	-0.251	0.802
Wvineyard	-0.002840	0.002910	-0.976	0.329
Westate	-0.005041	0.006958	-0.725	0.469
W91	0.004330	0.003961	1.093	0.274
W92	0.005426	0.003932	1.380	0.168
W93	0.004184	0.003838	1.090	0.276
W94	0.000396	0.004063	0.097	0.922
W95	0.004902	0.003704	1.323	0.186
W96	0.007315	0.004023	1.818	0.069
W97	0.005953	0.003750	1.587	0.112
W98	0.005384	0.003793	1.419	0.156
W99	0.004595	0.003845	1.195	0.232
CONSTANT	0.239430	0.001707	140.300	0.000

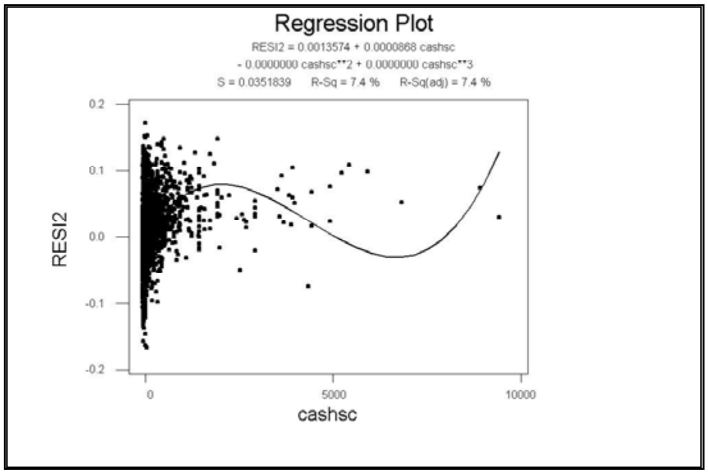
Table 8. OLS Coefficients for the Mid-up Price Segment

Name	Estimated Coefficient	St. Err.	T-Value	P-Value
Scscore	-0.001454	0.000078	-18.690	0.000
Scscore2	-0.000071	0.000012	-6.019	0.000
Agesc	-0.001848	0.000410	-4.503	0.000
agesc2	0.000383	0.000308	1.245	0.213
Lncas	0.002897	0.000178	16.280	0.000
Napa	-0.004784	0.001360	-3.518	0.000
Bay Area	-0.001354	0.001597	-0.848	0.397
Sonoma	-0.001103	0.001341	-0.822	0.411
South Coast	0.001470	0.001437	1.023	0.306
Carneros	-0.000863	0.001541	-0.560	0.575
Sierra Foothills	-0.000369	0.001963	-0.188	0.851
Mendocino	0.001963	0.001652	1.188	0.235
Nonvarietal	-0.012070	0.001115	-10.820	0.000
Pinot Noir	-0.011222	0.000716	-15.680	0.000
Cabernet	-0.010599	0.000795	-13.340	0.000
Merlot	-0.007700	0.000790	-9.751	0.000
Shyrah	-0.001860	0.000963	-1.932	0.053
Reserve	-0.005124	0.000677	-7.569	0.000
Vineyard	-0.002809	0.000535	-5.252	0.000
Estate	-0.002608	0.001609	-1.622	0.105
91	0.012314	0.001328	9.272	0.000
92	0.011904	0.001269	9.380	0.000
93	0.011560	0.001174	9.845	0.000
94	0.011763	0.001087	10.820	0.000
95	0.009264	0.001029	9.000	0.000
96	0.006993	0.000989	7.069	0.000
97	0.006964	0.000953	7.305	0.000
98	0.004078	0.001011	4.033	0.000
99	0.002942	0.000954	3.085	0.002
Wa	0.010007	0.002556	3.915	0.000
Wscscore	0.000331	0.000220	1.508	0.132
Wscscore2	-0.000005	0.000023	-0.216	0.829
Wagesc	0.002380	0.001158	2.055	0.040
Wagesc2	-0.000991	0.000814	-1.218	0.223
Wlncas	-0.001008	0.000563	-1.790	0.074
Wnonvarietal	-0.006643	0.002852	-2.329	0.020
Wpinot	0.013392	0.002933	4.566	0.000
Wcabernet	0.002929	0.002472	1.184	0.236
WMerlot	0.001375	0.002340	0.587	0.557
Wshyrah	-0.006579	0.002383	-2.761	0.006
Wreserve	0.003040	0.001778	1.710	0.087
Wvineyard	-0.000206	0.001357	-0.152	0.879
Westate	0.003214	0.004089	0.786	0.432
W91	0.004052	0.002815	1.439	0.150
W92	-0.002023	0.003191	-0.634	0.526
W93	-0.005352	0.002993	-1.788	0.074
W94	-0.011891	0.002997	-3.968	0.000
W95	-0.006211	0.002642	-2.351	0.019
W96	-0.006092	0.002786	-2.187	0.029
W97	-0.003769	0.002726	-1.382	0.167
W98	-0.005971	0.002583	-2.311	0.021
W99	-0.005729	0.002387	-2.400	0.016
CONSTANT	0.187940	0.001613	116.600	0.000

Table 9. OLS Coefficients for the Fine Price Segment

Name	Estimated Coefficient	St. Err.	T-Value	P-Value
Scscore	-0.001683	0.000156	-10.790	0.000
Scscore2	-0.000269	0.000026	-10.350	0.000
Agesc	-0.001750	0.000952	-1.839	0.066
agesc2	-0.001085	0.000538	-2.016	0.044
Lncas	0.001846	0.000335	5.517	0.000
Napa	0.001875	0.002234	0.839	0.402
Bay Area	0.003642	0.002579	1.412	0.158
Sonoma	0.005726	0.002238	2.558	0.011
South Coast	0.012455	0.002543	4.898	0.000
Carneros	0.004229	0.002497	1.694	0.090
Sierra Foothills	0.014397	0.003121	4.612	0.000
Mendocino	0.011830	0.003022	3.914	0.000
Nonvarietal	-0.020959	0.002314	-9.056	0.000
Pinot Noir	-0.008387	0.002087	-4.018	0.000
Cabernet	-0.013333	0.002105	-6.334	0.000
Merlot	-0.006532	0.002209	-2.957	0.003
Shyrah	-0.000292	0.002516	-0.116	0.907
Reserve	0.004380	0.001017	4.307	0.000
Vineyard	-0.001707	0.000964	-1.771	0.077
Estate	-0.000221	0.002059	-0.107	0.915
92	-0.000205	0.003152	-0.065	0.948
93	0.003067	0.002709	1.132	0.258
94	0.004983	0.002235	2.230	0.026
95	0.006571	0.001885	3.485	0.001
96	0.006463	0.001831	3.529	0.000
97	0.003832	0.001608	2.383	0.017
98	-0.003847	0.001603	-2.400	0.016
99	0.000503	0.001470	0.343	0.732
Wa	0.018165	0.004854	3.742	0.000
Wscscore	0.001551	0.000958	1.618	0.106
Wscscore2	0.000152	0.000131	1.160	0.246
Wagesc	-0.000129	0.001678	-0.077	0.939
Wagesc2	0.004257	0.001862	2.287	0.022
Wlncas	-0.003036	0.001044	-2.909	0.004
Wnonvarietal	0.012498	0.002853	4.381	0.000
WMerlot	-0.003915	0.003321	-1.179	0.239
Wshyrah	-0.016526	0.003638	-4.542	0.000
Wreserve	-0.003897	0.003806	-1.024	0.306
Wvineyard	0.007479	0.002799	2.671	0.008
Westate	-0.000736	0.003983	-0.185	0.853
W93	-0.002501	0.007003	-0.357	0.721
W94	-0.004814	0.004964	-0.970	0.332
W95	-0.015962	0.006002	-2.660	0.008
W96	-0.009921	0.005267	-1.883	0.060
W97	-0.009990	0.003569	-2.799	0.005
W98	-0.004809	0.003226	-1.491	0.136
W99	-0.004338	0.002863	-1.515	0.130
CONSTANT	0.145430	0.002897	50.200	0.000

Figure1-2. Excluded variable residual plots: cubic and nonparametric fit (I will edit these if we decide to keep them in)



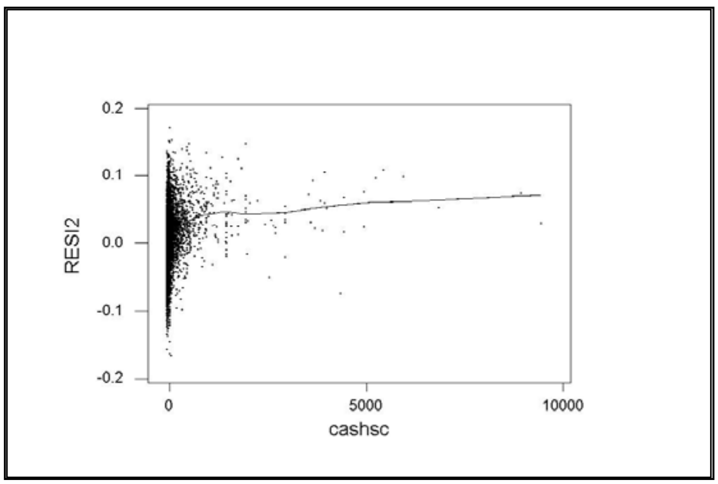


Figure 3. Estimated marginal implicit prices of number of cases produced for wines in the inexpensive, mid-low, mid-up and fine wines price segments (confidence bands omitted for clarity)

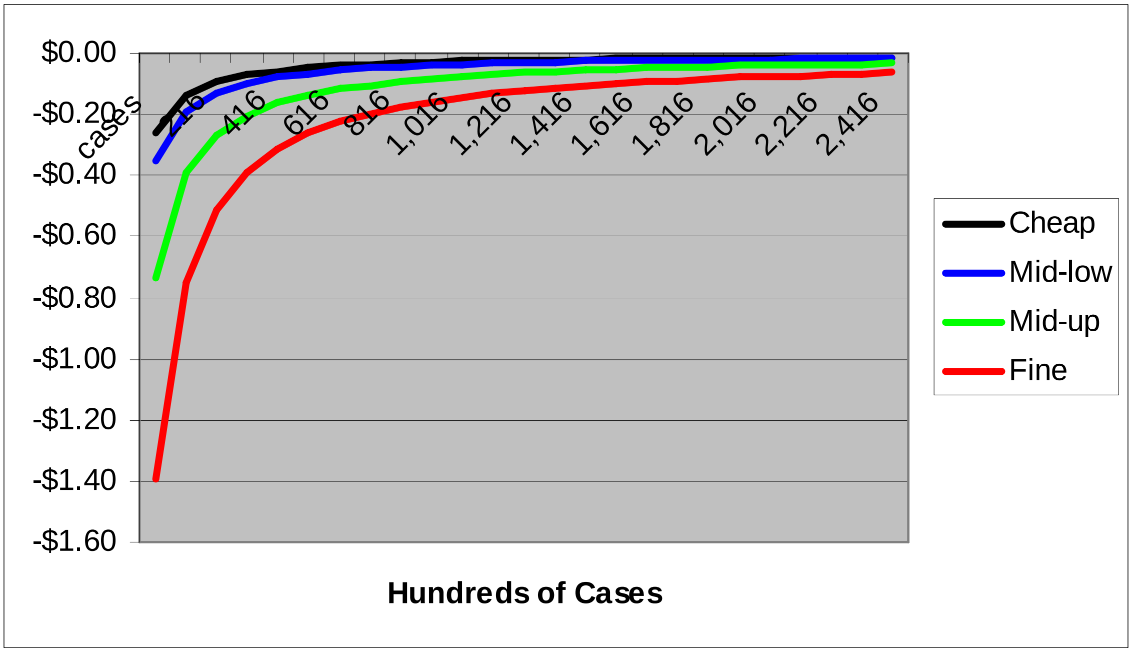


Figure 4. Estimated marginal implicit prices of score ratings in the *Wine Spectator* magazine for wines in the inexpensive, mid-low and mid-up price segments with 95 % confidence bands

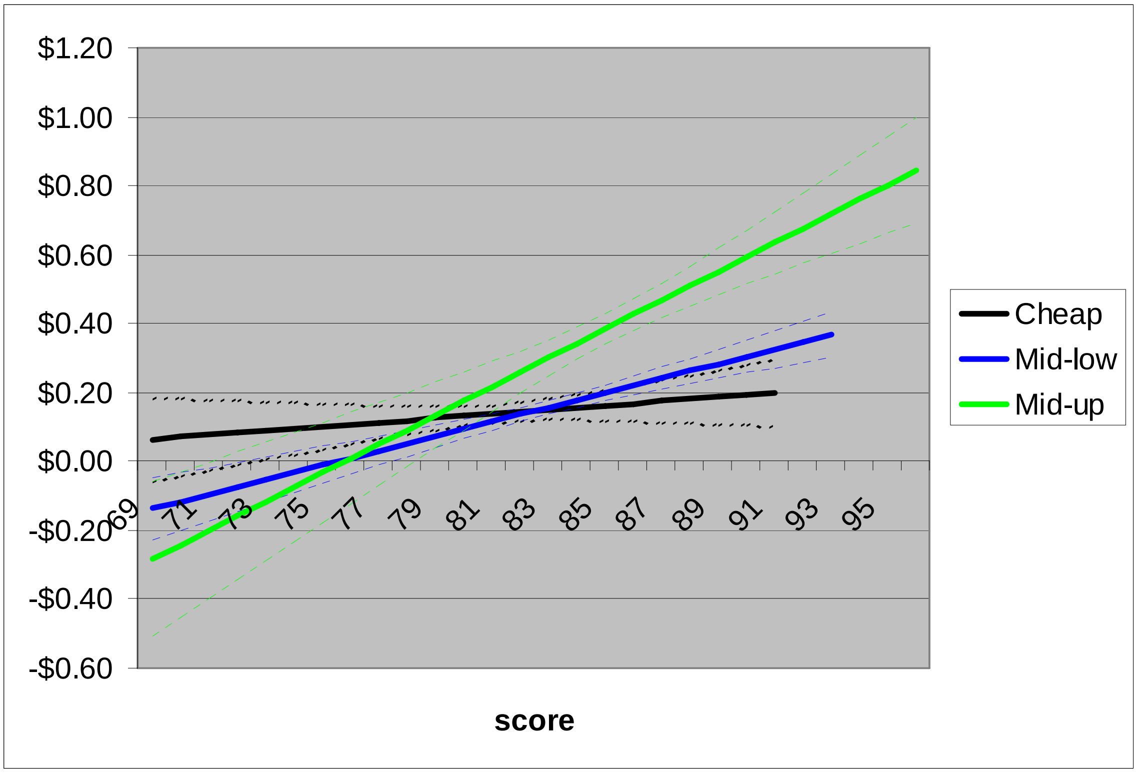


Figure 5. Estimated marginal implicit prices of score ratings in the *Wine Spectator* magazine for wines in the fine wines price segments with 95 % confidence bands

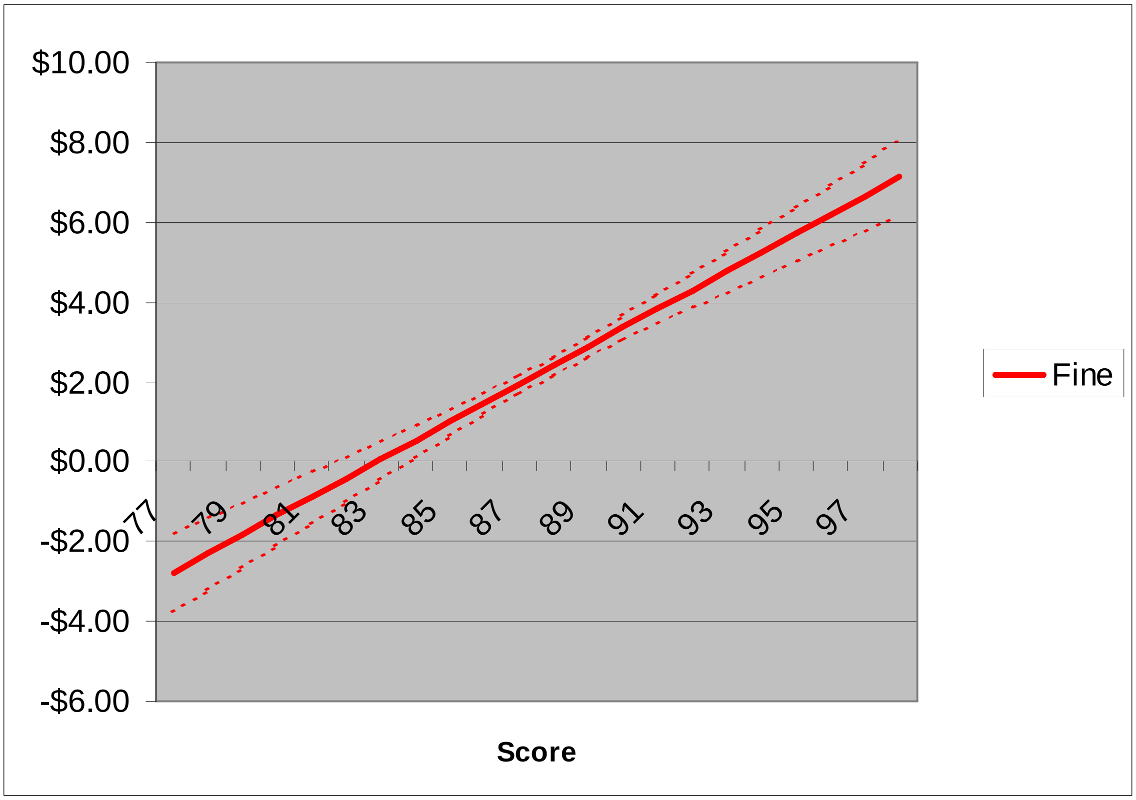


Figure 6. Estimated marginal implicit prices of years of years of aging for wines in the inexpensive, mid-low and mid-up price segments with 95 % confidence bands

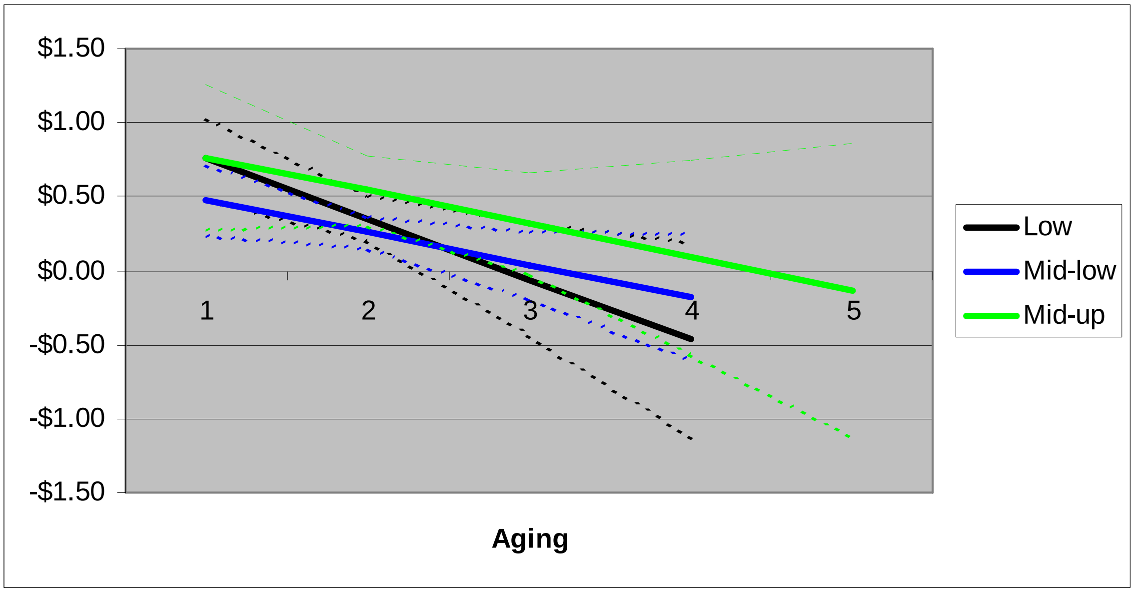


Figure 7. Estimated marginal implicit prices of years of aging for wines in the fine price segment with 95 % confidence bands

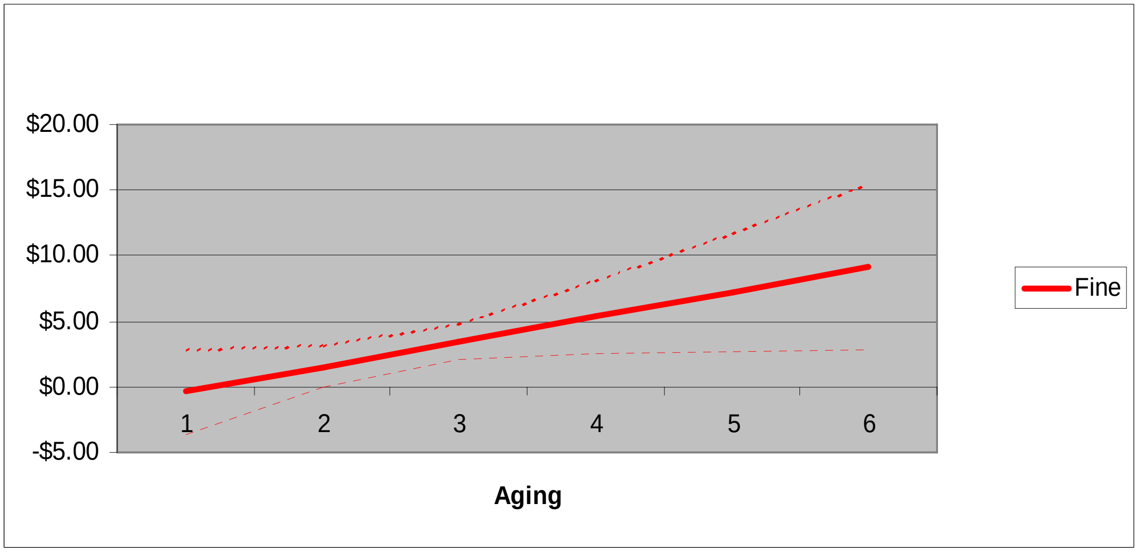


Figure 8. Estimated price premia of California and Washington regions of production with 95% confidence intervals for wines in the inexpensive, mid-low, mid-up and fine price segments (excluded variable: non-appellation California)

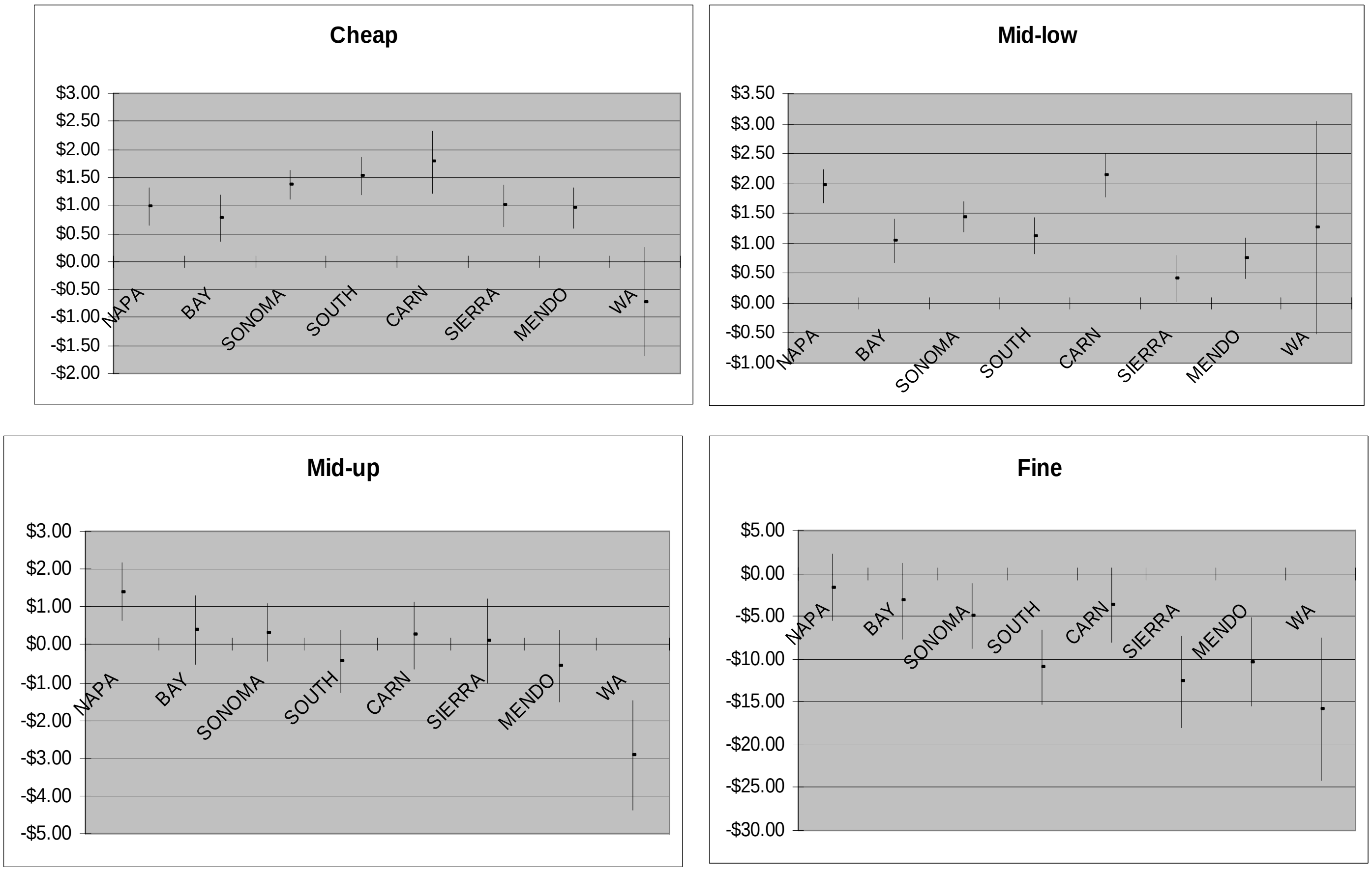


Figure 9. Estimated price premia for “reserve”, “estate”, and name of the vineyard label information with 95% confidence intervals for wines in the inexpensive, mid-low, mid-up and fine price segments

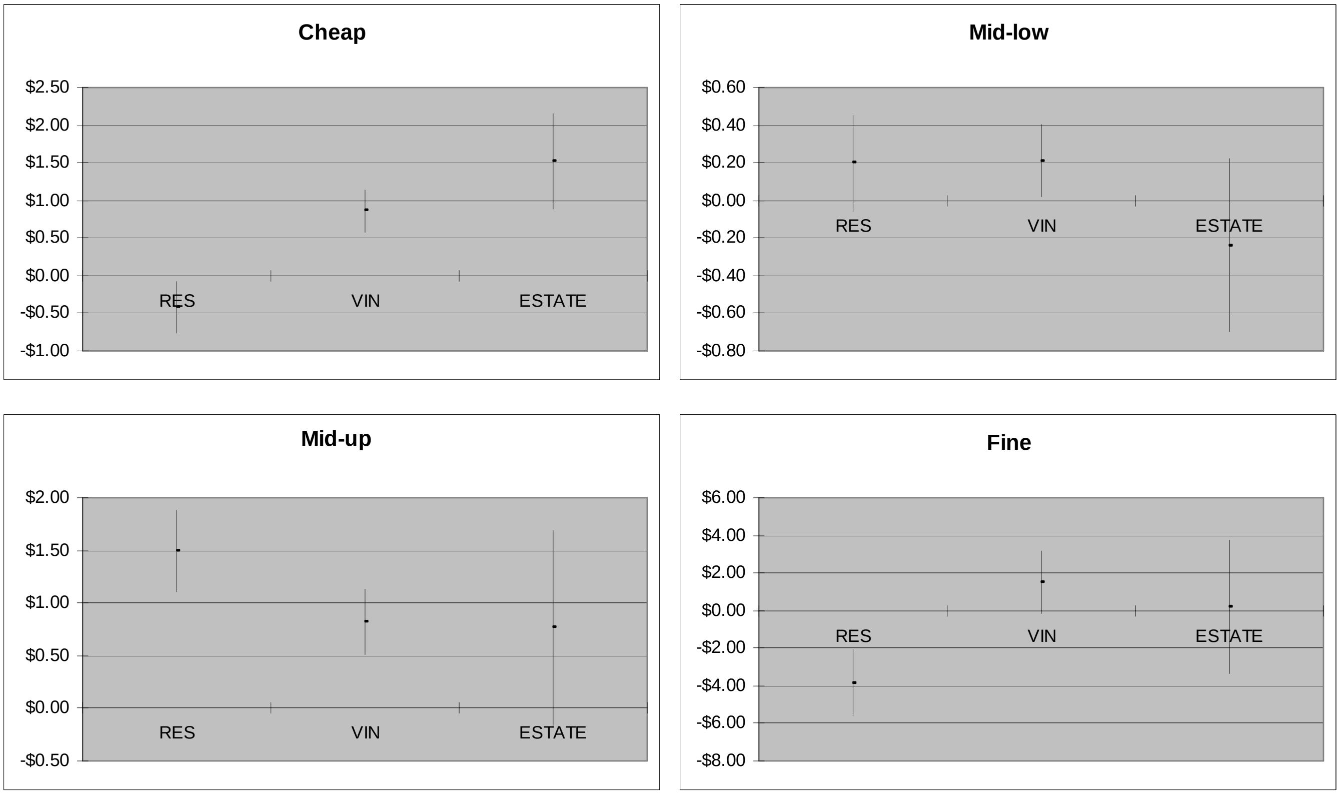


Figure 10. Estimated price premia of nonvarietal wines and Pinot, Cabernet, Merlot and Syrah grapes with 95% confidence intervals for wines in the inexpensive, mid-low, mid-up and fine price segments (excluded variable: Zinfandel)

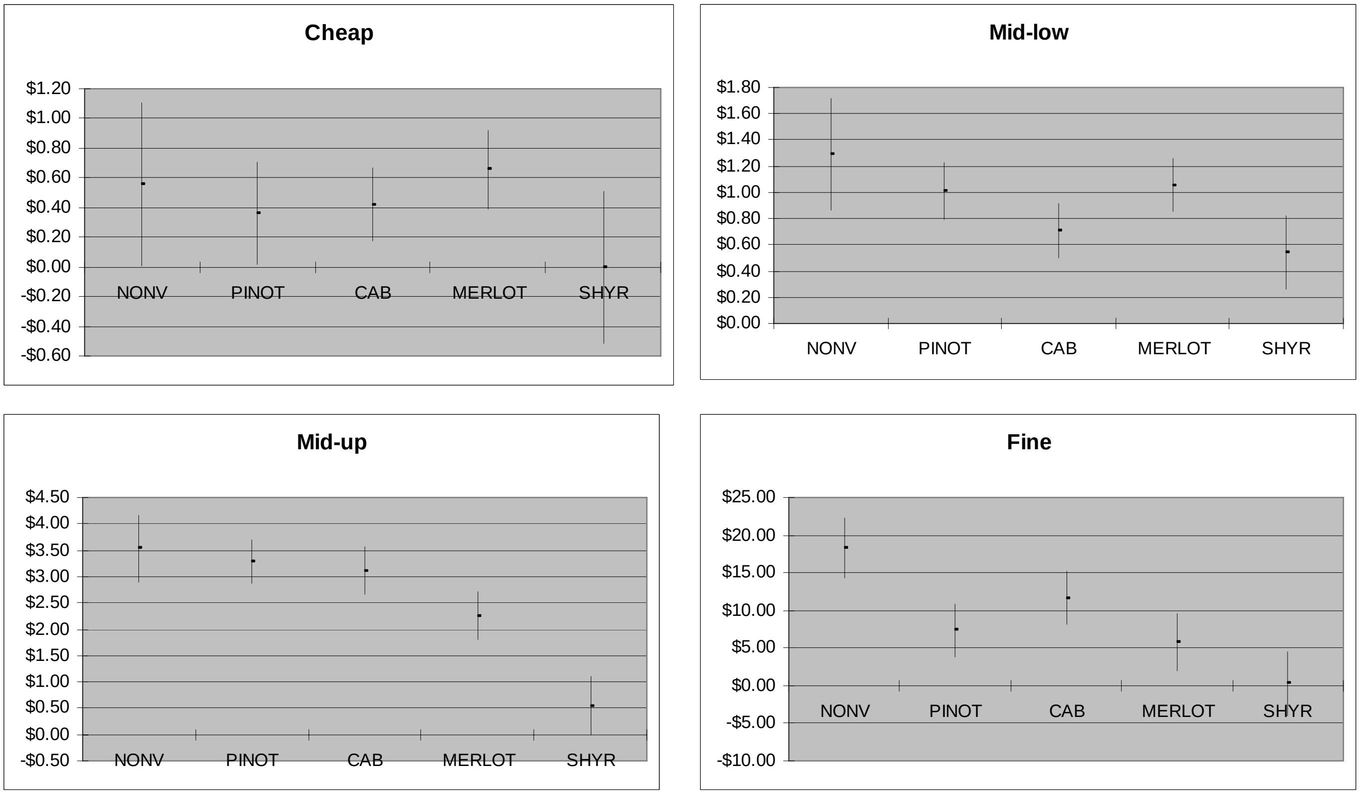


Figure 11. Marginal implicit prices of years of aging for wines in the inexpensive, mid-low, mid-up and fine price segments with 95 % confidence bands estimated using the pooled regression approach

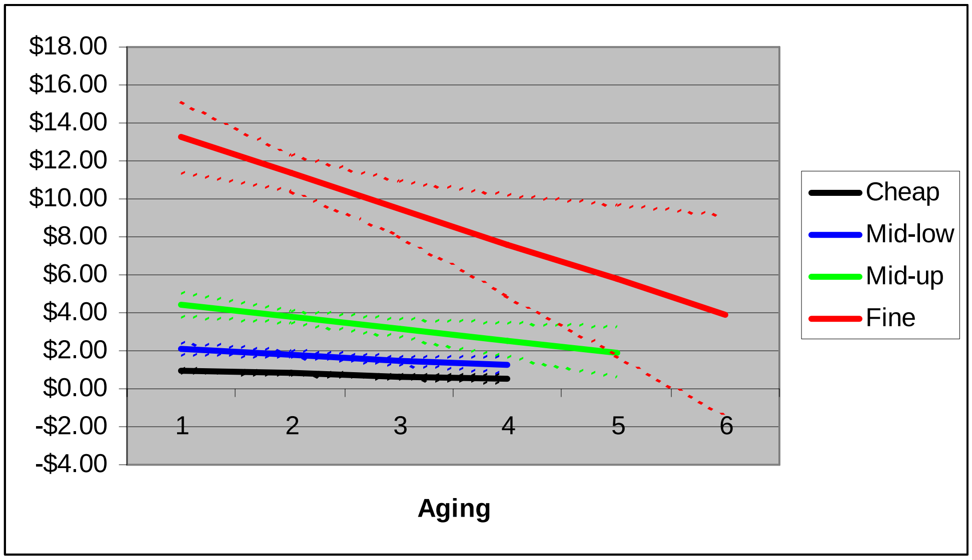


Figure 12. Price premia of California and Washington regions of production with 95% confidence intervals for wines in the inexpensive, mid-low, mid-up and fine price segments (excluded variable: non-appellation California), estimated using the pooled regression approach