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Impacts of Expert Information on Prices for an Experience Good across Product Segments: Tasting Notes and Wine Prices

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When purchasing experience goods, consumers often rely on information from expert evaluations. In this article, we quantify how expert information impacts prices across product segments. For higher-end products, consumers have the incentive to invest more time in research prior to purchase. Thus, expert evaluations should have a greater impact on the price of higher-end segments. We analyze the effects of tasting notes on wine prices across price categories and find that certain keywords used in tasting notes to describe wine characteristics exert a significant influence on wine prices. These effects vary across different segments, with the greatest impact on the premium segment.

Key words: expert evaluation, hedonic prices

Introduction

Understanding the process of price formation is difficult in the case of experience goods, which do not allow consumers to observe their quality prior to consumption. Hence, many consumers rely on information from expert evaluations when making purchasing choices. The use of expert information should depend on the benefits from product knowledge versus expending time acquiring and processing information. Since consumers have heterogeneous preferences for quality and face different costs of acquiring and processing information, expert information will not impact all shoppers but may be useful to specific market segments. One would expect that consumers who are paying high prices for quality will acquire more information. The objective of this article is to examine how expert information impacts prices across product segments. We accomplish this objective using the case of the wine market by measuring the impact of tasting notes on wine prices across price categories.

In the case of wine, expert opinions generally come in two forms: expert blind rating scores and tasting notes. Rating scores are numerical summary information and are low-cost for the consumer to process. In contrast, tasting notes are qualitative (Storchmann, 2012) and more costly for the consumer to obtain and process. The impact of information format has been studied in nutrition information. Berning, Chouinard, and McCluskey (2008) examine how detailed information compares with summary information in its impact on choice. Different consumers prefer different formats based on their costs of information processing and the consequences of the information.

Since wine quality cannot be assessed until after consumption, there is an element of risk in purchasing a bottle of wine. Costanigro, McCluskey, and Mittelhammer (2007) argue that for an

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experience good, such as wine, the magnitude of risk increases with price and decreases with information. For inexpensive wines, the risk is limited by the relatively low price. For more expensive wines, consumers have an incentive to invest more time on research prior to purchase. High-end wine consumers are more likely to read wine reviews and tasting notes. Thus, we expect tasting notes to have a greater impact on the price of high-end wines than on lower-end wines.

Consumers can reduce the risk of choosing nonpreferred wines by using experts' sensory descriptors to guide their purchase decisions. Lehrer (1975), Lawless (1984), and Weil (2007) conclude that the majority of people rely on experts when choosing wines. Charters and Ali-Knight (2000) find that consumers consider simple taste and smell descriptors to be important label information for wine choice. Tuorila et al. (1998) find that ratings of unfamiliar foods are enhanced when the products are described using positive information. These studies support the argument that overall sales are enhanced by descriptors (Thomas et al., 2014).

Many researchers make the case that expert wine ratings are suspect as objective measures of wine quality for many reasons, including that most wine product characteristics are "horizontal" rather than "vertical" quality attributes. This means not all consumers will agree on what constitutes quality. For example, some consumers prefer sweeter wines and some prefer drier wines. Expert ratings are based on experts' preferences. For example, highly influential wine critic Robert Parker has "a preference for powerfully concentrated fruity wines... [resulting in] some producers around the world feel[ing] compelled to customize their wines for his palate" (Asimov, 2006, p. 1). For expert wine ratings to be an objective measure of quality, consumers' wine preferences would need, on average, to be consistent with those of the experts creating the ratings.

There are sensory and psychological reasons to question the validity of expert wine ratings as objective quality measures. Even experts struggle with evaluating sensory differences in wines and often are influenced by context (Lehrer, 2012). Thus, for example, dying a white wine red with an odorless, tasteless food coloring will dramatically change experts' descriptions of that wine (Morrot, Brochet, and Dubourdieu, 2001). The tongue and the nose are the least sensitive of the five human senses and are physically incapable of detecting all of the combinations of notes that experts claim to be able to sense (Gürbüz, Rouseff, and Rouseff, 2006). Ratings vary not just by expert but also by the same expert when given the chance to (blindly) rate a bottle again, even when the review is done in the same day (Hodgson, 2008). From a psychological perspective, revealing a wine's (false) appellation dramatically changes experts' descriptions (Wansink, Payne, and North, 2007). Increasing the price of a wine increases how good people rate its taste to be (Plassmann et al., 2008). More generally, marketing placebo effects can alter consumption enjoyment (Enax and Weber, 2015).

Regardless of their value as objective measures of quality, experts' rating scores impact wine prices.[1] Hilger, Rafert, and Villas-Boas (2011) provide the most convincing evidence for the effect of scores on wine demand. They conducted a field experiment in California in collaboration with a national grocery retailer. At the treatment stores, randomly selected wines were given shelf labels with an expert rating score. The same wines were tracked at control stores over the same time period. Using scanner sales data, they used a difference-in-difference approach to test whether consumers responded to the scores. They find that at treated stores, low-scoring wines experienced a decrease in demand and high-scoring wines experienced an increase in demand.

It is uncertain whether expert ratings influence prices because consumers believe experts' opinions are good proxies for quality or because of their marketing effect. Combris, Lecocq, and Visser (1997, 2000) show that when regressing documented characteristics (such as expert scores, vintages, and sensory characteristics) on wine price, the documented cues are significant, while sensory variables (such as tannin content and other measurable chemicals) are not. Recent studies indicate that wine experts' opinions play a significant role in the perception of wine quality and

[1] Many studies—including Landon and Smith (1997); Combris, Lecocq, and Visser (1997, 2000); Oczkowski (1994); Schamel and Anderson (2003); Steiner (2004); Angulo et al. (2000); Waldrop, McCluskey, and Mittelhammer (2017)—support the finding that expert ratings are significant and should be included when modeling wine prices.

in the consumer decision-making process. Moreover, those opinions influence the final price of wines by providing an expert's signal of quality (Chocarro and Cortiñas, 2013; Dubois and Nauges, 2010; Goldstein et al., 2008; Ali, Lecocq, and Visser, 2008; Lecocq and Visser, 2006; Lima, 2006; Ramirez, 2010).

Demand for expert opinions has been increasing in consumer and producer decision making. In particular, Chocarro and Cortiñas (2013) investigate the impact of expert opinions or recommendations on consumer evaluations of wine. They conclude that recommendations from experts' ratings affect consumers' preferences. Ashenfelter and Jones (2013) assess whether consumers demand expert opinions because of their accuracy and find that expert opinions do not incorporate all public information that is useful in making predictions. Specifically, adding publicly available weather information improves experts' price predictions. Goldstein et al. (2008) point out that wine prices and expert recommendations might be poor guides for nonexpert wine consumers who care about the intrinsic qualities of wine. Ashton (2012) suggests that expert ratings can provide information on wine attributes, despite wide variations in the quality of wine judging.

Only Ramirez (2010) investigates the impact of wine experts' tasting notes on prices by using the number of characters of analytical and nonanalytical words defined by *Wine Spectator*'s wine glossary in the sample of tasting notes. He finds that the length of the tasting notes significantly affects wine prices. Durham, Pardoe, and Vega-H (2004) offer the first study to estimate the impact of wine menu descriptions on wine purchases.

There is empirical evidence that the effect of expert rating scores on price depends on price level. Costanigro, McCluskey, and Goemans (2010) show that the price premiums from lagged expert ratings tend to migrate from the region level to the firm level as wine prices increase. Their explanation is based on search costs: If search costs are large enough, consumers will trade the increased accuracy of learning about a specific wine's reputation for the convenience offered by more aggregated reputations (i.e., "collective reputations"), such as regions.[2] For high-priced, high-end wines, the consumers' cost of being wrong in their expectations about quality increases, so consumers are more likely to be willing to incur search costs and seek out expert rating scores on specific wines.

The current article contributes to this literature in a few ways. First, we estimate differential impacts to expert information across price segments. We include both quantitative (summary) ratings and qualitative evaluations in the analysis. Finally, in the case of wine, we quantify the effects of specific terms used in expert tasting notes on prices across price categories.

Modeling Framework

We use the hedonic price model (Rosen, 1974) to examine how tasting notes influence wine prices. Hedonic price analysis is based on the hypothesis that consumer utility is not generated by the purchased product itself but rather by the qualities and characteristics the product contains. Differentiated goods are treated as bundles of various quality attributes, which separate them from other, related goods, and the observed equilibrium market price is a function of the implicit prices of each quality attribute. By regressing price on the attributes, the hedonic functions provide estimates of the implicit price impact of each characteristic on the equilibrium price, embedding both supply and demand factors (Nerlove, 1995).

Wine price, P, is assumed to be described by a hedonic price function, $P = P(x)$, where x is a vector of attributes. The hedonic price of an additional unit of a product characteristic is calculated as the partial derivative of the hedonic price function with respect to that particular attribute. Each consumer chooses an optimal bundle of characteristics and all other goods in order to maximize utility subject to a budget constraint. In equilibrium, for continuous variables, each consumer's

[2] Many studies (Schamel and Anderson, 2003; Steiner, 2004; Costanigro, McCluskey, and Mittelhammer, 2007; Carew and Florkowski, 2010) have found that particular production regions have a *ceteris paribus* premium that captures the value of a region's collective reputation.

Table 1. Summary Statistics of the Quantitative Explanatory Variables (N = 6,085)

Variables	Mean	Median	Std. Dev.	Min.	Max.
P	30.17	27	17.341	5	185
Rating	88.88	89	2.992	68	98
Aging	3.05	3	0.772	1	7
Number of Cases	5,503.91	495	29,697.280	17	580,000

Source: www.winespectator.com (database).

chosen bundle will result in his or her indifference curve being tangent to the price gradient, $\partial P/\partial x_j$, for each attribute. Therefore, the marginal willingness to pay for a change in a wine characteristic is equal to the derivative of the hedonic price function with respect to that attribute. For discrete variables, finite differences $\Delta P/\Delta x_j$ 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 $P = P_m(X)$ for $P \in (1_m, h_m], m = 1, \ldots, s$, 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 $\partial P_m/\partial x_j$ or $\Delta P_m/\Delta x_j$ for market segment m.

Data

The dataset is composed of 6,085 observations from 16 years (1997–2013) from *Wine Spectator* Magazine (online version) for Washington red wines. The quantifiable variables include price, expert rating, the number of cases produced, years of aging before commercialization, and six sensory features from the notes. Wine prices are set by individual wineries, not by *Wine Spectator* staff or blind tasters. Therefore, the process of price determination and tasting note formation are independent of each other. The prices are set before the publication of tasting notes. *Wine Spectator* employs a "single-blind" methodology, which means that their tasters know general context information—such as vintage, appellation, and grape variety—but not the individual winery or the price (Shanken and Matthews, 2012).[3]

We utilize the expert ratings as an expert measurement of quality. We assume that consumers' quality assessments are, on average, consistent with *Wine Spectator*'s experts. We use the price (U.S. dollars per 750 ml bottle), the expert rating, the content of tasting notes, and the number of cases produced from 6,085 red wines in the sample. Four of the explanatory variables are nonbinary: price of the wine adjusted to 1997 values with the consumer price index (CPI) for alcohol, *P*; score obtained in the expert sensory evaluation provided by *Wine Spectator*, *Rating*; the natural logarithm of the number of cases produced, *Cases*; and the years of aging before commercialization, *Aging*. Descriptive statistics for variables are reported in Table 1, and Table 2 presents the explanatory variables and abbreviations with a short description of the variables used.

We select five representative American viticultural areas (AVAs) from the state of Washington, which represent over 91% of sales in that state: Columbia Valley, Horse Heaven Hills, Red Mountain, Walla Walla Valley, and Yakima Valley. Columbia Valley is the largest region in Washington and produces many varieties of wines, especially commercial wines (77.3% of Washington commercial wines) and semi-premium wines (67.7% of Washington semi-premium wines). AVA_j are indicator variables for the j AVAs. Almost 5.49% of the wines include the term "reserve" on their labels, mainly in the semi-premium and premium wine categories. Reserve is an indicator variable equal to 1 if the word "reserve" is reported on the label and 0 otherwise.

[3] For more information on *Wine Spectator*'s tasting procedures, see Shanken and Matthews (2012).

Table 2. Explanatory Variable Descriptions

Variables	Description
Rating	Rating score from Wine Spectator (on a scale of 0–100), centered by subtracting its mean
Rating^2	Rating squared
Aging	Years of aging before commercialization, centered by subtracting its mean
Aging^2	Aging squared
Cases	Natural logarithm of the reported total number of cases produced for each wine
AVAs	Indicator variables for American Viticultural Areas, equal to 1 if the wine is from the AVA in question and 0 otherwise
Columbia Valley	
Horse Heaven Hills	
Red Mountain	
Walla Walla Valley	
Yakima Valley	
Tasting Note Keywords	
Cherry	Equal to 1 if the word is present in the tasting note, and 0 otherwise
Spice	
Tannin	
Currant	
Finish	
Berry	
Reserve	Equal to 1 if "Reserve" was reported on the label, and 0 otherwise
97, . . . , 13	Indicator variables for each vintage

Experts use adjectives to describe the attributes and characteristics of wine. Following Durham, Pardoe, and Vega-H (2004),[4] we choose the six most-common sensory characteristics to test our hypotheses. These red wine keywords appear with over 10% frequency in the text of tasting notes based on sensory terminology: Finish (75.12%), Spice (20.07%), Currant (28.30%), Berry (57.65%), Cherry (32.29%), and Tannin (36.20%). $Notes_k$ are indicator variables for the presence of each keyword from the tasting notes. Two examples of tasting notes written by the same reviewer with similar ratings show the comparison for sensory characteristics (underlined):

Tasting Note 1 (2010 Syrah from Columbia Valley winery Charles Smith, rated 97):

> Rich, expansive and distinctive, dripping with endlessly deep blackberry, black cherry and pomegranate flavors, with broad hints of mineral, tar and spice that just don't quit as the finish rolls on, unimpeded by tannins. Complex and seductive, this can go on forever. Drink now through 2020. 65 cases made. –HS

Tasting Note 2 (2008 Syrah from Yakima Valley winery Efeste, rated 95):

> Focused, sharply defined and beautifully expressive, this packs an enormous range of red berry, pomegranate, tomato leaf and roasted beet flavors into a taut, savory jet of

[4] Durham, Pardoe, and Vega-H (2004) conclude that there are five sensory characteristics common to both red and white wines—Body, Finish, Oak, Rich, and Spices—and six sensory characteristics unique to red wines—Currant, Berry, Cherry, Chocolate, Tannin, and Vanilla.

deliciousness. Stylish, balanced and raucous all at the same time. Drink now through 2018. 385 cases made. –HS

The mean price of a bottle in the data (adjusted to year 1997 dollars) is $30.17, and the most expensive bottle released was priced at $185. The average wine rating score of the sample is 88.88, considered representative of a high-quality wine. Two bottles of wines had the highest rating of 98. The standard deviation of the number of cases made is quite large. This means that our sample includes several wineries that produce large quantities as well as some small winemakers. The wines from the sample have been kept in a barrel and stored in a cellar for an average of 3 years after bottling before commercialization.

Empirical Methodology

Using the hedonic price approach, we estimate different hedonic price functions for product segments in the red wine category. As differentiated products become increasingly different, it no longer makes sense to conclude that the marginal implicit prices are equal across products. For example, red and white wines are not generally combined in hedonic price estimations. One reason is that aging is valued in red wines but not in white wines. Straszheim (1974) argues that it is appropriate to segment markets for purposes of hedonic price estimation. Freeman (1993) makes the case that two conditions must be met for different hedonic price functions to exist: i) either the structure of demand, the structure of supply, or both is different across segments and ii) purchasers in one segment do not participate significantly in other segments. There must be some barrier that prevents arbitrage in response to differences in implicit prices.

Costanigro, McCluskey, and Mittelhammer (2007) make the case that wine meets both of Freeman's conditions. First, supply differs across segments because of i) limited land in locations with the highest reputations and ii) differing land values across growing regions. The structure of demand also differs across segments. Hall, Lockshin, and Barry O' Mahony (2001) find that consumers seek different characteristics, or value the same characteristics differently, depending on the occasion. Higher wine prices indicate higher quality to the consumer; consumers perceive price to reflect quality wines, which are used for more momentous occasions. Second, fine wines are typically sold in wine stores or at wineries and not in grocery stores, where more inexpensive wines are sold. Following Costanigro, McCluskey, and Mittelhammer (2007), we divide the sample into four market segments: commercial wines (price less than $13, 684 products), semi-premium ($13–$21, 1,268 products), premium ($21–$40, 2,818 products), and ultra-premium (greater than $40, 1,315 products).

Hedonic price theory does not offer guidance on functional form. Therefore, the econometrician typically relies on the data to inform the statistical fit. Within the hedonic pricing model, we evaluate functional forms by comparing linear, log-linear, power transformations, and optimal Box–Cox transformations of the dependent variable (prices) in the model to find the best-performing transformation in which parameters maximize a likelihood function based on a normality assumption (Box and Cox, 1964; Cleveland and Devlin, 1988; Landon and Smith, 1997; Costanigro and McCluskey, 2011). For pooled and segmented models, we implement a power transformation of price from the estimated Box–Cox parameter λ, where $\lambda = -0.069$. We use the goodness-of-fit (Jarque–Bera) test in our inverse transformation model, and the skewness and kurtosis match a normal distribution. The covariance matrix of the parameters is estimated using White's consistent heteroskedasticity-robust estimator to correct heteroskedastic residuals.

Quadratic rating and aging terms are added to the model based on their quadratic relationship with wine prices. We estimate following hedonic price function:

$$(1)\quad \begin{aligned} P_i^{\lambda} &= \alpha_0 + \alpha_1 Rating_i + \alpha_2 (Rating_i)^2 + \alpha_3 Aging_i + \alpha_4 (Aging_i)^2 + \alpha_5 Reserve_i \\ &+ \sum_{j=1}^{5} (\alpha_{5+j}) AVA_{ji} + \sum_{k=1}^{6} (\alpha_{10+k}) Notes_{ki} + \alpha_{17} Cases_i + \sum_{l=1}^{16} (\alpha_{17+l}) Year_{li} + \varepsilon_i. \end{aligned}$$

where ε_i is a random error term.

If wines with high rating scores sell for higher prices, then one would expect the marginal effect of ratings to be positive. However, Lecocq and Visser (2006) argue that the relationship between ratings and price is far from perfect. Therefore, the issue of whether this marginal effect is positive, negative, or statistically indistinguishable from 0 is purely empirical. Another variable is the number of cases made. All else constant, a larger supply of a particular wine should be associated with a lower price per bottle (Haeger and Storchmann, 2006). On the demand side, the marginal effect of the number of cases made is expected to be negative because consumers value rarity. Aging also plays an important role in wine price. Traditionally, red wine is stored in oak barrels for about 3 years while it ferments or ages before being commercialized or bottled. However, aging depends on the wine, the vintner, and whether the wine is made in a region where barrel aging is dictated. Wine producers usually use the term "reserve" on wine labels to show excellent rather than ordinary wines. The AVA[5] is a grape-growing region distinguishable by geographic features so that winemakers can create wines with recognizable character in terms of geology and climate.

Estimation Results

Table 3 presents the hedonic price regression results for the pooled (single hedonic function) and segmented models. The value of the adjusted R^2 statistic increases from 0.61 for the pooled model to 0.89 for the segmented model. We capture the specifics of each wine class by separating different market segments and accordingly increase the overall explanatory power of the hedonic model (Straszheim, 1974; Costanigro, McCluskey, and Mittelhammer, 2007). Table 4 presents the marginal effect estimates for the pooled and segmented models. Table 5 reports the Chow test results from testing the hypothesis that the regression coefficients are equal across the price segments. All test results reject the null hypothesis,[6] which means that the explanatory variables have different impacts on different price categories.

In the hedonic price technique, implicit marginal prices of characteristics for continuous variables are found by taking the derivative of price with respect to that variable. Since the power transformation of price (λ) is negative, a negative coefficient implies a positive marginal implicit price. Thus, when we interpret the results in Table 3, a negative coefficient implies a positive marginal effect of the attribute on wine prices, and vice versa based on the transformation of the dependent variable. The *Rating*, *Rating*^{2}, *Aging*, *Reserve*, and *AVA*s as wine characteristics have statistically significant coefficients. Prices increase in ratings at an increasing rate, implying that wines with higher ratings have additional premium values. Aging has a significant positive effect on the wine prices almost across market segments. However, prices increase in aging at a decreasing rate, indicating diminishing marginal returns to aging wines.

[5] As of April 2018, Washington State comprises 14 official AVAs: Ancient Lakes, Columbia Gorge, Columbia Valley, Horse Heaven Hills, Lake Chelan, Lewis Clark Valley, Naches Heights, Puget Sound, Rattlesnake Hills, Red Mountain, Snipes, Mountain, Wahluke Slope, Walla Walla Valley, and Yakima Valley. We selected five representative Washington AVAs that comprise 91% of sales in the state: Columbia Valley, Horse Heaven Hills, Red Mountain, Walla Walla Valley, and Yakima Valley.

[6] Chow test indicates a significant difference at 1% level for all null hypothesis testing across price segments.

Table 3. Estimation Results for Pooled and Segmented Hedonic Price Functions (coefficient × 10^2)

		Segmented			
Covariate	**Pooled**	**Commercial**	**Semi-Premium**	**Premium**	**Ultra-Premium**
Constant	74.800***	81.530***	80.670***	78.480***	75.910***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.003)
Rating	−0.409***	−0.282***	−0.105***	−0.086***	−0.108***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rating^2	−0.022***	−0.013***	−0.006***	−0.007***	−0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Aging	−0.638***	−0.177***	−0.039	−0.161***	−0.319***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Aging^2	0.220***	0.046	0.027	0.065***	0.069*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Reserve	−0.571***	−0.666	−0.236***	−0.016	−0.551***
	(0.001)	(0.005)	(0.001)	(0.001)	(0.001)
Columbia Valley	−0.450***	−0.872***	0.028	−0.053	−0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Horse Heaven Hills	−0.700***	−1.335***	0.068	0.060	−0.121
	(0.001)	(0.004)	(0.001)	(0.001)	(0.002)
Red Mountain	−1.391***	−1.019*	0.282**	−0.425***	−0.056
	(0.001)	(0.005)	(0.001)	(0.001)	(0.002)
Walla Walla Valley	−1.463***	−1.156	−0.187*	−0.315***	−0.272
	(0.001)	(0.009)	(0.001)	(0.001)	(0.002)
Yakima Valley	−0.813***	−0.748***	−0.005	−0.296***	−0.225
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Cherry	0.012	−0.132	0.015	−0.084**	0.093
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Spice	0.193***	0.053	0.042	0.078*	0.024
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Tannin	−0.328***	−0.019	0.024	−0.060*	−0.155**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Currant	0.021	−0.130	0.016	0.039	0.028
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Finish	0.016	0.038	0.115***	0.030	0.104
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Berry	0.107*	0.082	−0.013	−0.033	0.020
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Cases	0.756***	0.275***	0.190***	0.123***	−0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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		Segmented			
Covariate	**Pooled**	**Commercial**	**Semi-Premium**	**Premium**	**Ultra-Premium**
97	2.973***	2.285***	0.393*	0.379	–
	(0.004)	(0.005)	(0.002)	(0.005)	–
98	2.558***	2.004***	0.059	0.568	1.502***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.005)
99	2.170***	1.953***	−0.035	0.678	1.510***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.004)
00	1.791***	1.686***	0.064	0.601	1.362***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.004)
01	1.664***	1.843***	0.152	0.636	1.053***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.004)
02	1.597***	1.887***	0.246	0.596	0.584*
	(0.004)	(0.005)	(0.002)	(0.005)	(0.003)
03	1.298***	1.858***	0.066	0.370	0.895***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.003)
04	1.351***	1.671***	−0.014	0.407	1.183***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
05	0.900**	1.842***	−0.247	0.325	0.910***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
06	1.048**	1.504***	0.070	0.332	0.692***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
07	1.016**	1.504***	0.196	0.410	0.876***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
08	0.706*	1.085**	−0.014	0.260	0.692***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
09	0.734*	1.604***	0.030	0.274	0.733***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
10	0.309	1.360***	0.067	0.141	0.517***
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
11	−0.197	1.093**	0.074	0.016	0.326*
	(0.004)	(0.005)	(0.002)	(0.005)	(0.002)
12	−0.250	0.783	−0.095	−0.247	–
	(0.004)	(0.005)	(0.002)	(0.005)	–
R^2	0.61		0.89		
No. of Obs.	6,085	684	1,268	2,818	1,315

Notes: Standard errors are in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. Omitted variable: year 2013. The adjusted R^2 corresponding to the prediction of prices across all market segments, and thus based again on the entire data set, was calculated by stacking the segmented datasets in a single (block diagonal) design matrix and estimating the segmented hedonic models simultaneously.

Table 4. Marginal Effect Estimates for Pooled and Segmented Hedonic Functions

Covariate	Pooled	Commercial	Semi-Premium	Premium	Ultra-Premium
Rating	1.880	0.915	1.425	2.108	2.848
Aging	2.843	1.383	2.155	3.187	4.307
Reserve	2.665	1.287	2.013	2.987	4.067
Columbia Valley	2.102	1.015	1.587	2.356	3.208
Horse Heaven Hills	3.269	1.578	2.469	3.665	4.990
Red Mountain	6.494	3.136	4.905	7.280	9.912
Walla Walla Valley	6.832	3.299	5.160	7.658	10.427
Yakima Valley	3.795	1.832	2.866	4.254	5.792
Cherry	−0.057	−0.027	−0.043	−0.064	−0.087
Spice	−0.903	−0.436	−0.682	−1.012	−1.378
Tannin	1.531	0.739	1.156	1.716	2.336
Currant	−0.099	−0.048	−0.075	−0.111	−0.151
Finish	−0.073	−0.035	−0.055	−0.081	−0.111
Berry	−0.499	0.241	−0.377	−0.559	−0.761
Cases	−3.532	−1.705	−2.668	−3.959	−5.391
97	−13.882	−6.702	−10.485	−15.560	−21.187
98	−11.943	−5.766	−9.020	−13.387	−18.228
99	−10.131	−4.891	−7.651	−11.356	−15.462
00	−8.365	−4.039	−6.318	−9.376	−12.767
01	−7.770	−3.751	−5.868	−8.709	−11.859
02	−7.459	−3.602	−5.634	−8.361	−11.385
03	−6.060	−2.926	−4.577	−6.793	−9.249
04	−6.309	−3.046	−4.765	−7.072	−9.630
05	−4.204	−2.030	−3.175	−4.712	−6.416
06	−4.893	−2.362	−3.695	−5.484	−7.468
07	−4.742	−2.290	−3.582	−5.316	−7.238
08	−3.297	−1.592	−2.490	−3.696	−5.032
09	−3.425	−1.654	−2.587	−3.839	−5.228
10	−1.444	−0.697	−1.090	−1.618	−2.203
11	−0.918	0.443	0.693	1.028	1.400
12	−1.167	0.563	0.881	1.308	1.781
No. of Obs.	6,085	684	1,268	2,818	1,315

Notes: Omitted variable: year 2013.

Table 5. Chow Test-Testing the Hypothesis of Parameters' Equality across Market Segment

	Semi-Premium	Premium	Ultra-Premium
Commercial	82.09***	197.29***	125.62***
	(0.000)	(0.000)	(0.000)
Semi-Premium		161.23***	225.26***
		(0.000)	(0.000)
Premium			165.99***
			(0.000)

Notes: p-values are presented in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

For higher-end wines, including the term "reserve" on the label significantly increases prices more than for other price segments. Thus, better quality wines usually come from specific AVAs and strong vintages and receive higher rating scores. For instance, a bottle of 2001 Colvin Winery Merlot from Walla Walla Valley with the a rating of 70 is $12, cheaper than the bottle of Seven Hills Merlot from Walla Walla Valley with a higher rating of 90 and price of $24.

Consistent with previous findings, the number of cases of wine produced shows a significant negative effect on wine prices, which means the price of wines decreases with rarity (Costanigro, McCluskey, and Mittelhammer, 2007). The term "cult wines," or "trophy wines," refers to rare wines that consumers will pay a lot for and are hard to get. The number of cases produced has an insignificant impact on ultra-premium wine prices.

Further, the representative AVAs from Washington have significant positive effects on wine prices in the pooled model. For the premium wines, the variables representing Red Mountain, Walla Walla Valley, and Yakima Valley AVAs have a positive influence on wine prices. For commercial wines, the variables representing Columbia Valley, Horse Heaven Hills, Red Mountain, and Yakima Valley AVAs have a positive impact on wine prices.

Tannin is one of the common oak influences that impart flavors and aromas to wines, bringing consumers a richer tasting wine. However, spice and berry sensory characteristics might reduce the value of wines. In the pooled regression, the use of the words "spice" and "berry" in tasting notes has significantly negative effects on wine prices, but "tannin" has a significant positive effect. The word "tannin" in tasting notes increases the value of wines, especially for high-end (ultra-premium and premium) wines. The "cherry" sensory characteristic has a significant positive effect on premium wine prices, but "spice" has a significant negative effect on wine prices in that segment. The "finish" sensory characteristic has a significant negative effect on the prices of semi-premium wines. For example, a bottle of 2008 Syrah from the Abeja winery in the Walla Walla Valley containing "spice" in the tasting note with a cost of $30 is cheaper than the bottle of 2010 Syrah from the Cayuse winery in the Walla Walla Valley containing "tannin" in the tasting note, which costs $75.

As expected, vintages have mixed effects on wine prices in the pooled model. The years 1997 through 2010 all have a negative effect on wine prices. Weather plays a significant role in the wine price and quality. For example, some studies show that wine prices, particularly for fine wine, are correlated with weather (Ashenfelter, Ashmore, and Lalonde, 1995; Byron and Ashenfelter, 1995). Other studies indicate that climate change will affect wine quality by changing grape ripening or maturation (Jones et al., 2005; Palliotti et al., 2014; Jones and Hellman, 2003). results suggest that vintage has mixed effects on wine prices due to unexpected weather conditions, which might cause lower-quality wines. However, only 2 years, 2011 and 2012, have a positive effect on wine prices in the pooled model, which suggests an upward general trend in the Washington wine price equilibrium.

We calculate the marginal effects shown in Table 4 for continuous linear variables as $\partial p/\partial x_i = (1/\lambda) \times \alpha_i \times (\alpha_0 + \alpha'\overline{X})^{(1/\lambda-1)}$ and for the continuous variables that include a quadratic term (e.g., rating and aging) as $\partial p/\partial x_i = (1/\lambda) \times (\alpha_i + 2\alpha_{i+1}x_i) \times (\alpha_0 + \alpha'\overline{X})^{(1/\lambda-1)}$. The marginal effects are reported for the average value of the variable in the product category. *Rating*, *Aging*, *Reserve*, and the *AVA* variables have positive marginal premiums across price segments. Thus, winemakers should consider the revenue implications of these marginal effects in conjunction with the corresponding marginal costs. There are some variables that the winemaker can directly control (e.g., aging, use of "reserve" on the label, and AVA choice) and other variables that the winemaker only influences indirectly through his or her winemaking (e.g., rating scores and tasting notes).

The direct marginal effects from years of aging are positive and concave with the greatest returns in the ultra-premium category at $4.31 for an additional year of aging. The marginal effect of aging for the pooled data is $2.84. Since the marginal effects from aging are concave, we can calculate the amount of aging at which the marginal returns to aging are 0. The optimal level of aging in terms of marginal effects is approximately 3.6 years for the ultra-premium category and falls to just below 2 years for the premium category and lower for the bottom two categories. A caveat is that there may also be indirect returns to aging through the rating scores and tasting notes. That is, a wine that is released too soon will likely receive lower rating scores.

The marginal effects from additional rating points are positive and convex, which means that there is no optimal level. In other words, the marginal effects of ratings increase at an increasing rate. The average ratings increase across product categories, so it is not surprising that the marginal effects of expert ratings increase as one examines more-expensive categories. The ultra-premium category benefits the most from the marginal effects of additional rating points, at $2.85. The marginal effect of ratings for the entire pooled dataset is $1.88.

The inclusion of “reserve” on the wine label has a positive marginal effect, with the highest value of $4.07 for the ultra-premium category. The Walla Walla Valley AVA receives the highest premium of $10.43 and $7.66 for ultra-premium and premium wines, respectively. The Red Mountain AVA is second, with marginal effects of $9.91 and $7.28 for ultra-premium and premium wines, respectively.

Winemakers can affect ratings through their winemaking practices and their choice of grapes (“terroir”). However, factors such as weather are beyond the winemaker’s control. Rating points increase in value as wines move up in price categories. The ultra-premium category commands the highest marginal effect of $2.85 in rating. In contrast, in the commercial category, the marginal effect for an additional rating point is $0.92.

As with quality ratings, the winemaker influences tasting notes through winemaking practices but cannot directly control them. The marginal effects of tasting notes differ across segments. For the premium category, when the tasting note “spice” is present, it has a negative marginal effect of $1.01, and the use of “cherry” has a small negative marginal effect of $0.06. The use of the word “tannin” in tasting notes brings a premium of $2.34 for ultra-premium and $1.72 for premium wines. In the semi-premium category, the only statistically significant marginal effect in tasting notes is the use of the word “finish,” which leads to a $0.05 discount. As previously mentioned, none of the six tasting note words are statistically significant for the commercial category.

Conclusions

This article investigates how expert information in the form of tasting notes impacts prices across product segments. We use tasting notes written for Washington red wines by *Wine Spectator* for 1997 to 2013 vintages. We estimate hedonic price regressions both for the entire dataset and for subsets of the data based on price categories. We find that certain keywords in the tasting notes deliver a significant effect on wine prices and that these effects differ across price segments. For higher-end products, consumers have an incentive to invest more time in research prior to purchase. Thus, we expected tasting-note evaluations to have a greater impact on price for higher-end segments. We find that the impact of tasting notes varies across price segments.

For commercial wines, none of the tasting-note variables are statistically significant. Only one tasting-note variable is statistically significant in the semi-premium category. The premium category has three statistically significant terms, while the ultra-premium category has one significant tasting-note term, “tannin.” We find that tasting notes have the greatest impact on the premium category. The importance of tasting notes on prices is not monotonically increasing in category as we originally hypothesized. It may be the case that consumers who buy ultra-premium wines gather information from additional sources that are not reflected in tasting notes. They may rely more on other information sources, such as their own tasting experiences and personal recommendations.

We argue that these results are consistent with our hypothesis that consumers will obtain more information prior to purchase for an experience good as the product becomes more expensive. For lower-priced wines, consumers will typically buy at a grocery store with only the label information available. Higher-end wine shoppers will value the information from tasting notes. Ultra-premium wine shoppers may visit the wineries in which they are interested and taste for themselves.

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