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Consumer sorting and hedonic valuation of wine attributes: exploiting data from a field experiment

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Abstract

This article uses a novel experimental approach to measure consumer willingness to pay (WTP) for wine attributes. We invited customers of a local supermarket who had selected a bottle of wine to purchase to participate in a valuation experiment. Integrating their original wine choice into the experiment, each participant evaluated six alternative wines, generating a rich set of data on willingness to pay and consumer characteristics. The data from the experiment allow us to compare standard shelf price-based wine attribute valuation estimates with estimates using WTP data and an increasing amount of information about individual consumers. The full model employs individual fixed effects to estimate WTP parameters without bias from consumer sorting or supply side influences. Our WTP estimates for wine attributes differ markedly from previous attribute value estimates. Consumers in our sample display clear and stable preferences for wine varieties, but less clear preferences for appellations. Our results suggest caution is needed in using market prices to estimate parameters of the consumer valuation function for product attributes.

JEL classifications: C93, D12, L66

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1. Introduction

Economists have used hedonic pricing to study the market value of attributes of products including cars, computers, and wine (see, for example, Bajari and Benkard, 2005; Griliches, 1961; Nerlove, 1995, respectively). Analyses of fundamental market conditions—such as consumer willingness to pay (WTP) for product attributes—are, however, frequently hindered by a paucity of data. As Oczkowski and Doucouliagos (2014) note, data generated during market transactions do not permit identification of WTP for product attributes. The estimation of WTP for attributes is complicated by the fact that the data used in most studies of attribute valuation are a product of both demand and supply, and may be affected by omitted variables and consumer sorting (Epple, 1987).

Experimental economics provides a toolset suited to generating data not usually available from market transactions. Experimental economic tools facilitate the study of WTP for product attributes by providing control over the choice environment and attributes observed by participants. Researchers have used these features in laboratory and field experiments to study consumer WTP for, typically, a small set of attributes.[1] While these auctions provide a valuable tool for eliciting WTP from consumers, the ability of these techniques to address data problems related to consumer sorting and omitted variables has not been fully leveraged.

In this article, we study consumer WTP for wine attributes using data generated in a field valuation experiment combining shoppers' uninfluenced original choice of a bottle of wine with six alternative wines randomly selected from the store's inventory to explicitly address consumer sorting and omitted variables. We connected participants' WTP for alternative wines, using a full bidding approach, to the shelf price of the originally selected wine by creating a trade-off between the original and alternative wines, and collected information on consumer characteristics, including demographic and wine choice-related variables.

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Data Appendix Available Online

A data appendix to replicate main results is available in the online version of this article.

[1] Lusk and Shogren (2007) provide a thorough overview of experimental auctions studies. See Lusk and Shogren (2007) Table 1.1 for a summary.

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Our experimental design permits us to examine how much people value wine attributes by comparing valuation estimates derived from commonly available price data to WTP estimates incorporating an increasing amount of information about consumers, culminating in a fixed effects model. Tying consumers' uninfluenced wine choices to WTP data in a binding economic experiment provides a unique opportunity to assess consumer self-selection into market segments, and marginal changes in valuation for alternative products in the product neighborhood. Naturally, our results apply specifically to wines in the price ranges we observed—primarily between $5 and $30—and are not necessarily applicable to other market segments.

Valuation estimates for wine attributes change when we use WTP, rather than market price, data. Applying standard hedonic models to price data, our estimates for appellation and grape variety correspond closely to past analyses of wine attribute valuation, with premia for prestigious appellations like Napa Valley and little variation in valuation for grape varieties (Bombrun and Sumner, 2003). Using WTP rather than price as the dependent variable begins to erode the high parameter estimates for appellations, but affects grape variety estimates less. Once we implement the full suite of econometric controls—including individual fixed effects—participants appear to have stronger preferences among grape varieties than appellations.

2. Applied hedonic pricing studies

Hedonic pricing models are used to estimate the value of attributes external to the good studied, such as the effect of access to parks on housing prices, as well as product attributes bundled in a good, for example the value of an extra year of age for a wine. Both external and bundled attributes have been widely studied. The housing literature has provided estimates of consumer valuation of externalities such as air pollution (Palmquist, 1984) and valuation of goods like school quality and neighborhood amenities (Bayer et al., 2007; Black, 1999). Consumer products examined include cars (Griliches, 1961), breakfast cereal (Stanley and Tschirhart, 1991), wine (Nerlove, 1995), and personal computers (Bajari and Benkard, 2005). Though economists frequently use hedonic pricing analysis, the conditions necessary to move beyond estimation of first-stage, implicit attribute prices occur infrequently.

The two main issues that researchers must overcome to accurately measure parameters of the value function—sorting and identification—have generated a significant literature (Bayer et al., 2007; Brown and Rosen, 1982; Ekeland et al., 2004; Epple, 1987). Sorting refers to correlations between consumer characteristics and product attributes that arise when differences in consumers' preferences for attributes lead them to locate themselves at particular places in the product space. Sorting is a problem for estimation if the characteristics or attributes that are correlated are unobserved. Sorting can lead to estimates conflating WTP for attributes with the influence of the unobserved consumer characteristic on WTP. Strategies proposed for recovering parameter estimates include quasi-experimental methods (Bayer et al., 2007; Black, 1999) and approaches that impose assumed distributions of preferences in the consumer population (Bajari and Benkard, 2005). The problem of identifying demand parameters separately from supply parameters in market-generated data is particularly complex for multi-attribute goods because attributes are bundled and in some cases may be difficult to measure or may be unobserved by the researcher.

While a large literature on wine valuation exists, authors have infrequently been able to move beyond estimating implicit marginal price of attributes, though a few argue they are able to. Obtaining data from the Swedish state alcohol importer, Nerlove (1995) estimated the demand elasticity for wine, arguing that the state monopoly on wine sales resulted in a completely elastic supply function. Ashenfelter (2008) paired bids for Bordeaux wines with weather data to predict wine prices and quality. Gergaud and Ginsburgh (2008) employed auction data to examine the effect of natural endowments and technology on wine quality. Ashenfelter and Storchmann (2010) studied the relationship between landscape features and vineyard prices in Germany to predict the effect of climate change, using the fixed supply of vineyard sites to identify the relationship between climate and wine attribute valuation. While these latter three papers permit observation of a price determined wholly within the context of the auction, additional product attributes such as reputation of the winery or production area may play an important role in valuation (Cross et al. 2011).

Much of the consumer-focused wine valuation research evaluates the effect of expert ratings on purchases or valuation. In a field experiment, Hilger et al. (2011) posted wine ratings in a supermarket and found that for low-priced wines, high ratings markedly increased purchases. Friberg and Grönqvist (2012) provided corroborating evidence on the role of wine experts, finding that positive reviews led sales to peak shortly after the review was released. Ali et al. (2008) exploited a change in one expert's schedule for releasing wine reviews to estimate the effect of ratings on pre-release prices in Bordeaux wines.

Research on wine attribute valuation is primarily dominated by hedonic pricing studies relying on wine publication data. Oczkowski and Doucouliagos (2014) review many of these articles in a meta-analysis of the price–quality relationship. Attributes typically examined include grape variety, appellation, vintage, expert rating, and number of cases produced (Bombrun and Sumner, 2003; Oczkowski, 2001; Schamel and Anderson, 2003). Occasionally chemical or sensory characteristics augment the set of attributes (Jones and Storchmann, 2001). Authors have interpreted their results differently: appellations, for instance, capture information about climate and soil conditions under which the grapes were grown, which affect the sensory qualities of the wines (Ashenfelter, 2008; Ashenfelter and Storchmann, 2010), but also accrue reputations, which influence consumers' valuation and purchasing decisions (Cross et al., 2011; Landon and Smith, 1998).

The price of the wine seems to matter for attribute valuation. Costanigro et al. (2007) find that segmenting wines by price and fitting separate hedonic pricing models within a segment yields different implicit attribute values. Costanigro et al. (2010) examine valuation of nested reputations—from appellation reputations to wineries' individual reputations. They show that as price increases, premia shift from appellations to wineries. Differing marginal attribute values by price segment likely reflect the interplay of supply and demand factors, including consumer sorting.

Researchers have also conducted experimental economic studies on wine. Lange et al. (2002) found that French consumers tasting five different bottles of Champagne blind did not evaluate them differently by hedonic rating scores or WTP. However, hedonic rating scores and WTP differed significantly for the bottles in two other conditions. Ratings and WTP were very similar between label only and tasting and label conditions, implying that the label information dominated the sensory information. In a study of low-priced wines, Combris et al. (2009) observed little differentiation in WTP. They argued that preference heterogeneity drove this outcome; when they examined WTP by ranking of the wines, they found marked differences. Grebitus et al. (2013) studied preferences for the distance that wines had been shipped. A literature using hypothetical discrete choice experiments has examined the effect on purchase intentions or liking of back label information (Mueller et al., 2010); objective wine attributes, such as brand, region, and awards (Lockshin et al., 2006); and packaging, labeling, and sensory attributes (Mueller and Szolnoki, 2010). Thiene et al. (2013) incorporated observed Prosecco choices into a stated preference framework. They used the pooled data to identify consumer segments and investigate attribute non-attendance in the Prosecco market.

3. Incorporating hedonic theory into a consumer valuation experiment

The consumer value function in Rosen (1974) informed the design of our experiment. The value function assigns a value to a bundle of product attributes at a reference utility level. Formally, wines can be described by a vector of attributes, **z**. Utility depends on the attributes of the wine consumed, and on consumption of a numeraire good, x. Utility, then, can be represented by U(**z**, x). Consumers choose a vector of wine attributes $\mathbf{z} = (z_1, \ldots, z_n)$ and quantity of the numeraire good, x, to maximize their utility, subject to a budget constraint. The value function, defining WTP for varying attribute amounts at a reference level of utility, for an individual with reference level of utility, u^0, is represented as $v(z| u^0) \equiv$ WTP—the price an individual is willing to pay for the bundle of attributes, z, at the reference level of utility.

For this experiment, the attributes, z^*, and shelf price $P(z^*)$ of the participant's original wine define the reference level of utility, u^*.[2] Because the experiment presented the alternative wines as substitutes for the original wine, participants' valuations of the alternative wines inherently refer to the level of utility, u^*. While our design purposefully builds in a tradeoff between revealed preferences and alternatives, others have noted that this connection between valuation of products offered in an experiment and market goods complicates interpretation of valuation data when researchers lack knowledge of relevant alternative market goods (Alfnes, 2009; Harrison et al., 2004).[3]

The WTP for the product when the first attribute, appellation—denoted z_1—changes from that of the chosen wine, $z_1{}^*$ (say, Napa Valley), to another value, $z_1{}'$, (Sonoma County), while holding all other variables constant, is $v_i(z_1', z_2*, \ldots, z_K * u_i*) = WTP_i'$. Participants' bids for the alternative wines represent their valuation of the alternative wines with respect to the reference level of utility provided by the original choice. Participants' WTP for wine attributes can be estimated from the regression of their bids on the vector of wine attributes, and consumer characteristics.

4. Experimental design and procedure

We collected WTP data using a design built on the demand-revealing Becker-DeGroot-Marschak mechanism (BDM) (Becker et al., 1964).[4] The BDM gave participants incentive to value alternative wines accurately for two reasons. First, participants faced potentially trading in their original wine, providing incentive not to overstate their WTP for the alternative wines. Second, the BDM discourages underbidding by separating consumers' bids from the randomly drawn "experiment price." If participants understated their WTP for the alternatives, they might have missed an opportunity to purchase the alternative at a price they would have been glad to pay.

A step-by-step description of the experiment is provided in appendix A. Participants were shoppers in a grocery store who had chosen a bottle of "red" or "white" American wine. When they had made a decision—moving away from the wine shelves with the bottle, or placing the bottle in their cart—a researcher

[2] Note that the outcome of the value function—or WTP—for the originally chosen wine at the reference utility level is the shelf price of the wine; this is because utility is defined over consumption of product attributes and the numeraire good. A lower market price results in greater consumption of the numeraire good, thereby increasing utility.

[3] Because we observed participants' optimal choice, we expect that the WTP bids elicited in the experiment for the alternative wines will not represent a "maximum" WTP, but will incorporate the surplus provided by the original choice.

[4] We chose the BDM rather than other demand-revealing valuation mechanisms (e.g., Vickrey or *N*th-Price Auctions) because we had one participant at a time, a situation for which only the BDM is appropriate. Additionally, we chose to use the BDM rather than two other valuation techniques that can accommodate single participants: choice experiments and BDM-style methods that elicit a range of WTP values (Wang et al., 2007). Choice experiments are less efficient and since we interacted with consumers who were shopping we did not have time to put participants through the number of choice scenarios needed to obtain enough data. Second, because participants were regular wine purchasers, the precision of their bids was less of a concern (Fischhoff, 1991); concerns about bid precision motivated techniques eliciting a range of values (Wang et al., 2007).

invited them to participate in the experiment. Participants received a $10 gift card to the store. While similar in design to Thiene et al. (2013) and Vestal et al. (2013), participants in our research made real, rather than hypothetical, choices. Participants submitted bids for six alternative wines drawn from the store's inventory; alternatives had shelf prices that were within three dollars of the original wine's shelf price.[5]

We considered consumer sorting on prices. Significant evidence exists suggesting consumers interpret price as a signal of quality (Bagwell and Riordan, 1991; Shiv et al., 2005). We held the shelf prices, but not bids, of the alternative wines that were selected for comparison to within three dollars of the shelf price of the original wine for two reasons.

First, we sought to avoid influencing WTP data through the anchoring and adjustment heuristic (Tversky and Kahneman, 1974). In situations of uncertainty, people may use a familiar price as an anchor for valuation (Ariely et al., 2003). Since participants had already chosen a wine (and considered its price) prior to the research, if they subsequently valued alternative wines with significantly different shelf prices, we would risk eliciting relatively meaningless bids. Shelf prices of participants' original choices were quite similar to average prices they reported paying for wine, making it even more likely that alternative wines with quite different shelf prices could be unfamiliar enough that participants might employ the anchoring and adjustment heuristic. Secondly, we felt that the unanticipated $10 coupon—a windfall—to the supermarket might make them more likely to "trade up" if they were asked to consider an alternative wine that was more expensive than they normally purchased. There is evidence that windfall gains are treated differently than money that is anticipated (Arkes et al., 1994).

4.1. Wine attributes studied

We studied twelve wine-producing regions in the United States, some of which were aggregates of smaller appellations, or regions. Table 1 presents information on the shelf prices of the wines—categorized by region—originally selected by participants and on the shelf prices of wines in the store's inventory.

We focused on seven grape varieties in our analysis—Cabernet Sauvignon, Chardonnay, Merlot, Pinot Grigio, Pinot Noir, Sauvignon Blanc, and Zinfandel. These seven varieties accounted for almost 60% of sales by volume of American-produced wines in the U.S. wine market (Nielsen Company, 2010), and 66% of sales by volume in the supermarket chain in which we conducted our experiment (Nugget Markets, 2007). We also included red blends and white blends. Less common red and white wine grapes were aggregated into Other Red and Other White categories for analysis, though participants saw the specific grape variety during the experiment. Table 2 presents data on the shelf prices of the participants' originally selected wines and on the wines in the supermarket's inventory, grouped by variety.

[5] We considered restricting alternative bottles to be the same color as the original bottle, and while there is a popular notion that red-wine drinkers will not drink white wine, for instance, we found no data addressing this assumption. We chose to present red and white wines as alternatives, permitting us to test the assumption. We intend to examine valuation differences between participants with revealed red and white wine preferences in a future paper.

Table 1
Shelf price of originally chosen wines and all wines in store inventory by appellation

	Originally chosen wine price (mean)	Store inventory price† (mean)
California	9.80	9.54
Central Coast‡	10.42	13.90
Central Valley§	14.48	14.19
Monterey Co.§	14.70	15.58
Napa Valley	18.54	42.02
Napa and Sonoma Sub Appellations	16.11	33.12
Oregon and Washington	15.74	25.27
North Coast§	14.04	15.22
San Luis Obispo Co.§	16.00	21.11
Santa Barbara Co.§	9.17	17.13
Sierra Foothills§	13.71	17.77
Sonoma Co.	12.47	18.11
Observations	250	975

Source: Experiment and Nugget Market Wine Inventory, March 2009.
Notes: Originally Chosen Wine Price is the shelf price of the bottle the participant had selected when approached to participate in the experiment. Store Inventory Price is the unweighted mean shelf price of the all of the wines available in the store for a particular appellation.
†Median shelf prices tended to be lower than mean shelf prices, particularly for the *Napa Valley* and the *Napa and Sonoma* sub-appellations.
‡*Central Coast* includes San Francisco and Santa Cruz appellations.
§The appellation variable includes all constituent sub-appellations.

Table 2
Shelf price of originally chosen wines and all wines in inventory by grape variety

	Originally chosen wine price (mean)	Store inventory price† (mean)
Cabernet Sauvignon	14.08	39.03
Chardonnay	12.69	18.40
Merlot	10.21	18.65
Other Red	14.06	18.76
Other White	12.20	12.09
Pinot Grigio	9.38	11.54
Pinot Noir	18.92	24.40
Red Blend	15.82	33.81
Sauvignon Blanc	12.00	13.25
White Blend	–	15.54
Zinfandel	14.51	20.45
Observations	250	975

Source: Experiment and Nugget Market Wine Inventory, March 2009.
Notes: Originally Chosen Wine Price is the shelf price of the bottle the participant had selected when approached to participate in the experiment. Store Inventory Price is the mean shelf price of the all of the wines available in the store, not weighted by sales value or volume.
†Median shelf prices tended to be lower than mean shelf prices, particularly for varieties *Cabernet Sauvignon* and *Red Blend*.

Table 3
Individual and aggregate winery variables in the experiment

Winery name variable	Number of observations	Criterion for inclusion
Infrequent	181	Wineryi ≤ 5
Somewhat frequent	56	6 ≤ Wineryi ≤ 10
Frequent	19	11 ≤ Wineryi ≤ 15
Individual Wineries		Wineryi ≥ 16
Beaulieu Vineyards	19	
Beringer	24	
Bogle	36	
Castle Rock	23	
Chateau Ste. Michelle	27	
Columbia Crest	29	
Cycles Gladiator	26	
Domaine Laurier	20	
Forestville	18	
Gallo	29	
Hahn	44	
Husch	17	
Kenwood	27	
Lava Cap	20	
McManis	18	
Moniz	22	
Napa Ridge	30	
Ravenswood	18	
Robert Mondavi	25	
Rominger West	16	
Rosenblum	18	
Sebastiani	20	
Sobon Estate	18	
Souverain	19	
Sterling vineyards	34	
Talus	20	
Toasted head	17	
Total wineries	283	

Source: Experiment.

Over 280 individual wineries were represented in the sample of original or alternative wines in the experiment.[6] To reduce the number of parameters to be estimated, we applied an aggregation criterion: wineries observed as original or alternative wines in the experiment more than 15 times were included individually in the analysis. Other wineries were aggregated into those appearing frequently (11–15 times), somewhat frequently (6–10 times) and infrequently (1–5 times). Table 3 presents information about winery name variables included in the analysis. The final wine attribute we considered was the age of the wine in 2009 (*WineAge*). Though expert rating has widely been found to be an important factor in wine sales (e.g., Friberg and Grönqvist, 2012; Hilger et al., 2011), most wines in the supermarket had not been rated, and less than 8% of participants indicated that expert rating influenced their original choice of wine. Therefore, we did not include expert rating in this research.

[6] The inventory at the supermarket in which we conducted this research comprised 975 separate U.S. wines produced by 419 wineries. Many of the wineries that did not appear in our data were sold at very high or very low prices and did not have enough alternative bottles within the price window to qualify for the experiment. In particular, the high end of the price distribution ($50 and above) contained a large number of unique wineries.

Table 4
Prices for original and alternative bottles of wine

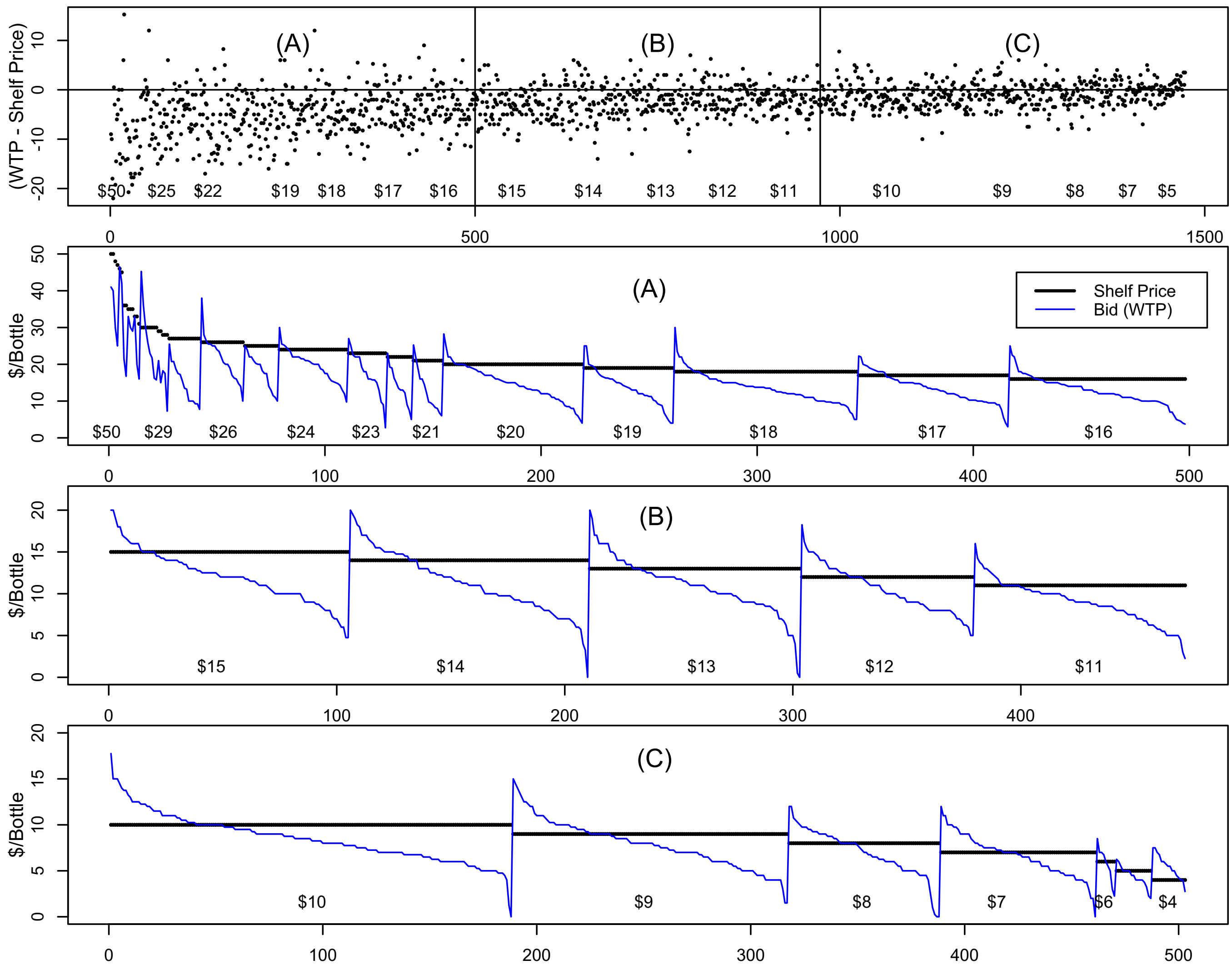
	Field experiment summary data	
	Participant-selected wine	Alternative wine
Observations	250	1500
Mean shelf price	13.85	14.02
Standard deviation	5.86	5.80
Minimum price	4.00	4.00
Maximum price	48.00	50.00
Mean WTP	–	11.19†
Standard deviation	–	5.37†
Minimum WTP	–	0.00
Maximum WTP	–	46.50

Source: Experiment.
†For 26 observations of WTP for the alternative wine, participants mistakenly failed to enter a bid. These observations were omitted from these calculations.

4.2. Descriptive statistics

We recruited 250 consumers in a Davis, California supermarket between March and June 2009. Home to a University of California campus, Davis is located within 60 miles of Napa, Sonoma, Central Valley, and Sierra Foothills wine-producing areas. We observed 250 uninfluenced, original wine choices and, with six alternative wines presented to each participant, 1,500 bids for alternative wines. Table 4 displays data on the wines originally selected by participants. The mean shelf price of the originally selected wines was $13.85. Alternative wines had slightly higher prices: $14.02. Mean WTP for the alternative wines was $11.19. Figure 1 presents the relationship between shelf prices and WTP for alternative wines. The top panel plots the difference between WTP and shelf price of the alternative wines (on the vertical axis) against the shelf price of the alternative wines (on the horizontal axis). Panels A, B, and C depict shelf prices and WTP for three price segments: (A) $16–$50, (B) $11–$15, and (C) $4–$10. These segments are also identified in the top panel. The solid black line represents shelf prices of alternative wines; the blue line tracks WTP for those alternative wines. It should be noted that these values are not conditioned on any independent variables; however, the figures demonstrate the diversity of WTP for alternative wines.

Table 5 reports selected participant demographic characteristics. Participants' mean number of 750-mL bottles of wine purchased monthly was 6.41. Participants reported spending an average of $13.12 per bottle, which was similar to the mean shelf price of $13.85 for the original bottles selected by participants. On average, participants had been buying wine for over 12.5 years. The gender, age, and educational profile of participants tracks closely with the adult population of Davis, California (U.S. Census 2010). Just over half—52%—of participants were female. On average, participants had completed more than a bachelor's degree and were 38.24 years old.



Source: Experiment.

Fig. 1. The relationship between shelf prices and bids for alternative wines. The top panel displays (WTP – Shelf Price), sorted on the x-axis by the shelf price of the original wine. Panels (A)–(C) plot shelf prices (black) and bids (blue) for each shelf price sorted high to low, corresponding to the top panel.

Mean household income was approximately $80,000 per year—nearly $20,000 per year more than the average Davis household at the time of the study (U.S. Census 2010).

5. Estimation strategy

We use data generated in the experiment to estimate WTP for wine attributes, and to examine how estimates change when we add controls for consumer characteristics and sorting into market price segments. We start with an analysis of marginal attribute prices as a comparison to previous hedonic pricing studies. Model code and data are available as a data appendix.

5.1. Estimating marginal attribute prices

To estimate marginal attribute prices, we regress the shelf price of each wine that appeared in the experiment as an original or alternative wine ($n = 877$) on the set of wine attributes:

$$Price_j = \beta_0 + \rho WineAge_j + \sum_{a=1}^{A} \beta_a DAppellation_{aj} + \sum_{v=1}^{V} \beta_v DVariety_{vj} + \sum_{w=1}^{W} \beta_w DWinery_{wj} + \varepsilon_j. \quad (1)$$

The equation relates $Price_j$, the shelf price of wine j, linearly to a constant term, the wine's age, the appellation and varieties of the wines, winery name, and an error term.

5.2. Estimating consumer WTP for wine attributes

We use 1,724 pooled observations of original and alternative wines to examine WTP for wine attributes. We first regress WTP on the same set of variables in (1) with the addition of a dummy variable for participants' originally chosen wines, *DOriginal*:

Table 5
Participant wine experience and demographic characteristics

Variable	Mean	Standard deviation
Bottles purchased/month (750 mL)	6.41	5.84
Price per bottle ($)	13.12	5.02
Wineries visited per year	3.73	22.36
Taken class on wine (0,1)	0.29	0.21
Read wine literature (0,1)	0.28	0.20
Female (0,1)	0.52	0.50
Age (in years)	38.24	14.48
Household income (INC) ($1000)	79.80	64.06
Years of schooling (EDU)	16.41	1.63

Source: Experiment.
Observations: 250.

$$WTP_{it} = \beta_0 + \rho WineAge_{it} + \sum_{a=1}^{A} \beta_a DAppellation_{ait} + \sum_{v=1}^{V} \beta_v DVariety_{vit} + \sum_{w=1}^{W} \beta_w DWinery_{wit} + \theta DOriginal_i + \varepsilon_{it}. \tag{2}$$

The dummy variable for the original wine captures differences in information and choice setting participants faced when evaluating the original and alternative wines.

We next add consumer characteristics, $\boldsymbol{\alpha}_{\mathbf{i}}$, including the demographic variables gender, age, education, and income, as well as wine-related variables:

$$WTP_{it} = \beta_0 + \rho WineAge_{it} + \sum_{a=1}^{A} \beta_a DAppellation_{ait} + \sum_{v=1}^{V} \beta_v DVariety_{vit} + \sum_{w=1}^{W} \beta_w DWinery_{wit} + \theta DOriginal_i + \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} \gamma_i \alpha_i + \varepsilon_{it}. \tag{3}$$

Finally, we leverage the panel structure of our data to include individual-specific fixed effects, which account for sorting and unobserved participant characteristics:

$$WTP_{it} = \beta_0 + \rho WineAge_{it} + \sum_{a=1}^{A} \beta_a DAppellation_{ait} + \sum_{v=1}^{V} \beta_v DVariety_{vit} + \sum_{w=1}^{W} \beta_w DWinery_{wit} + \theta DOriginal_i + \lambda_i ID_i + \varepsilon_{it}, \tag{4}$$

where ID_i is an individual-specific dummy variable. Results from WTP regressions are reported with individual-specific cluster robust standard errors.

6. Results and discussion

Table 6 presents estimates from regressions of (a) shelf prices on wine attributes; (b) WTP on wine attributes; (c) WTP on wine attributes and participant characteristics; and (d) WTP on wine attributes and individual fixed effects to control for sorting and individual-specific characteristics. We focus on a few important wine attributes throughout the discussion to compare the change in value and WTP estimates as more control is added to the analysis.

6.1. Marginal attribute prices

The marginal attribute price results (Table 6, column 1) show significant dispersion in implicit attribute prices. The parameter estimate for *WineAge* indicates that each additional year of age was worth $0.65. Four variety variables—*Cabernet Sauvignon, Pinot Noir*, *Other Red Varieties,* and *Zinfandel*—were valued significantly more than the reference category, *Sauvignon Blanc*. The estimates imply that the value of *Pinot Noir*, featuring the highest premium, is $4.46 more than *Sauvignon Blanc* in the market.

Appellation value estimates are generally consistent with previous research. All the appellations had statistically significant positive parameter estimates compared to the omitted appellation, *California*. *Napa Valley* had the highest premium, at $9.87. *Napa and Sonoma sub-appellations* ($8.93) and the aggregate variable *Oregon and Washington* ($6.77) had the next highest marginal prices.

Winery values were estimated in reference to *Beaulieu Vineyards*. Six wineries had significant parameter estimates at standard levels ($p \leq 0.05$), while another five were marginally significant. Only one of the six—*Rosenblum*—commanded a price premium in the market relative to *Beaulieu*. None of the aggregate winery variables was significant.

The results of the marginal attribute price analysis are similar to findings in Bombrun and Sumner (2003), the study with the product set closest to ours. They analyzed suggested retail prices for 8460 California wines from 1989 to 2000, finding that the *Napa Valley* appellation was priced $5.99 higher than the *California* appellation. In their study, most grape varieties were not significant, though *Pinot Noir* was valued significantly higher than *Merlot*, their omitted category—a result we also find.

6.2. Consumer WTP: wine attributes only

Using WTP as the dependent variable yielded results similar to the analysis of marginal attribute prices. *WineAge* remained statistically significant—and nearly identical to 6a—with

Table 6
Valuing of appellation, variety, winery name, and wine age attributes

	Conventional hedonic analysis (6a: shelf price)	WTP (6b: WTP)	WTP with consumer characteristics (6c: WTP)	WTP with individual fixed effects (6d: WTP)
Intercept†	3.93** (1.82)	3.75** (1.30)	7.91** (2.89)	21.05** (0.94)
WineAge‡	0.65** (0.19)	0.61** (0.17)	0.56** (0.15)	0.09 (0.11)
Cabernet Sauvignon	2.32** (0.78)	2.15** (0.70)	2.39** (0.70)	0.60 (0.50)
Chardonnay	0.45 (0.76)	0.72 (0.59)	1.23** (0.59)	−0.11 (0.43)
Merlot	1.55* (0.88)	1.50** (0.66)	1.88** (0.65)	0.44 (0.59)
Pinot Grigio	1.03 (1.14)	0.70 (0.69)	1.12 (0.75)	0.63 (0.66)
Pinot Noir	4.46** (0.90)	4.72** (0.75)	4.75** (0.75)	2.12** (0.60)
Other Red Varieties	1.81** (0.91)	2.15** (0.61)	2.19** (0.62)	0.30 (0.55)
Other White Varieties	−0.06 (1.06)	0.84 (0.65)	1.45** (0.69)	0.01 (0.55)
Red Blend	1.65 (1.00)	1.82** (0.81)	1.75** (0.78)	−0.67 (0.60)
White Blend	1.46 (1.76)	0.27 (1.23)	0.65 (1.27)	−1.32 (0.97)
Zinfandel	2.78** (0.85)	2.52** (0.71)	2.53** (0.62)	0.28 (0.47)
Central Valley§	4.24** (0.82)	1.89** (0.53)	1.77** (0.50)	−0.16 (0.39)
Central Coast¶	4.10** (0.96)	1.54** (0.67)	0.82 (0.70)	0.39 (0.56)
Monterey§	4.27** (1.15)	3.43** (0.77)	2.97** (0.71)	1.26* (0.68)
Napa Valley	9.87** (0.67)	6.54** (0.79)	5.25** (0.68)	0.66 (0.50)
Napa & Sonoma Sub-AVAs	8.93** (0.66)	5.92** (0.75)	5.19** (0.65)	0.84* (0.50)
North Coast§	4.38** (1.02)	1.80** (0.65)	1.39** (0.62)	−0.14 (0.62)
Oregon/Washington	6.77** (1.13)	4.47** (1.09)	3.72** (1.08)	1.09* (0.62)
San Luis Obispo§	5.40** (1.04)	4.35** (0.72)	3.89** (0.77)	0.73* (0.41)
Santa Barbara§	3.37** (1.19)	1.39 (0.88)	0.88 (0.84)	0.67 (0.60)
Sierra Foothills§	4.44** (0.88)	2.47** (0.50)	1.81** (0.57)	0.03 (0.50)
Sonoma County	5.93** (0.88)	3.73** (0.69)	2.81** (0.64)	0.30 (0.51)
Infrequent Wineries	3.20* (1.63)	1.65* (0.88)	1.68* (0.86)	−0.21 (0.61)
Somewhat Frequent	1.45 (1.64)	0.47 (0.73)	0.68 (0.75)	−0.21 (0.61)
Frequent	1.55 (1.68)	−0.10 (0.74)	0.02 (0.77)	−0.80 (0.62)
Beringer	1.29 (2.09)	0.46 (1.05)	0.78 (1.04)	−1.11 (1.14)
Bogle	1.76 (2.01)	1.13 (1.01)	1.41 (0.99)	−0.60 (0.74)
Castle Rock	−3.75* (2.23)	−4.05** (0.94)	−3.47** (1.06)	−1.84** (0.87)
Chateau Ste. Michelle	−0.36 (2.45)	0.01 (1.35)	0.36 (1.47)	−0.69 (0.93)
Columbia Crest	−4.49* (2.33)	−3.13** (1.56)	−2.40 (1.68)	−0.80 (1.33)
Cycles Gladiator	−4.11* (2.34)	−2.60** (1.24)	−1.75 (1.28)	−1.06 (1.15)
Domaine Laurier	−7.61** (2.46)	−5.39** (1.10)	−4.17** (0.98)	−0.13 (0.82)
Forestville	−5.10** (2.50)	−3.25** (0.93)	−2.40** (1.00)	0.29 (0.84)
Gallo	−5.50** (2.42)	−4.68** (0.98)	−3.66** (1.03)	−1.40 (0.87)
Hahn	3.26 (2.27)	2.01 (1.25)	1.94 (1.18)	0.00 (0.93)
Husch	2.15 (2.60)	3.38** (1.09)	3.32** (1.04)	1.17 (0.93)
Kenwood	−0.68 (2.11)	−0.85 (0.95)	−0.71 (1.04)	0.08 (0.89)
Lava Cap	0.70 (2.52)	0.93 (1.05)	0.97 (1.10)	0.20 (0.93)
McManis	2.69 (2.75)	1.48* (0.88)	1.44 (0.95)	−0.89 (0.80)
Moniz	−2.07 (3.02)	−1.35 (1.20)	−0.76 (1.27)	−0.22 (1.11)
Napa Ridge	−7.54** (2.63)	−6.10** (1.03)	−5.05** (1.00)	−0.58 (0.94)
Ravenswood	0.74 (2.20)	0.04 (1.17)	0.38 (1.17)	−0.56 (0.78)
Robert Mondavi	−0.27 (2.17)	−0.45 (0.99)	−0.10 (1.08)	−0.32 (0.98)
Rominger West	5.89* (3.09)	3.28* (1.90)	2.74 (1.81)	−0.67 (1.75)
Rosenblum	7.76** (2.20)	3.56* (2.07)	2.78 (1.72)	−0.65 (1.12)
Sebastiani	−3.13 (2.69)	−2.17* (1.18)	−1.14 (1.15)	0.21 (1.02)
Sobon estate	−0.90 (2.88)	−0.34 (1.16)	0.11 (1.10)	0.05 (0.93)
Souverain	−0.02 (2.81)	−0.45 (1.26)	0.13 (1.26)	−0.31 (0.92)
Sterling	1.08 (2.04)	2.16** (1.08)	2.17** (1.01)	0.46 (0.82)
Talus	−7.21** (2.41)	−4.90** (1.05)	−4.21** (1.13)	−0.76 (0.83)
Ventana	1.80 (2.72)	−0.88 (1.30)	−0.70 (1.23)	−1.11 (1.25)
Original		2.40** (0.26)	2.40** (0.25)	2.54** (0.24)
Bottles purchased/month			−0.05 (0.04)	
Price per bottle			0.14** (0.06)	
Wineries visited/year			0.03 (0.06)	
Taken class on wine			1.26** (0.54)	
Read wine literature			0.59 (0.64)	
Female			−0.30 (0.42)	

(*Continued*)

Table 6
Continued

	Conventional hedonic analysis (6a: shelf price)	WTP (6b: WTP)	WTP with consumer characteristics (6c: WTP)	WTP with individual fixed effects (6d: WTP)
Age			0.01 (0.02)	
Household income			0.006 (0.004)	
Years of schooling			-0.41^{**} (0.18)	
R^2	0.47	0.36	0.42	0.79
Adj. R^2	0.43	0.34	0.40	0.75
AIC/AICc	5,241/5,249	10,111/10,114	9,960/9,965	8,681/8,810
Observations	877	1,724	1,724	1,724

Source: Experiment. Reported values are the estimated coefficient and, in parentheses, standard errors. The standard errors in columns 2, 3, and 4 are cluster robust.
Significance: $^{**}P \leq 0.05$; $^{*}P \leq 0.10$.
The data used for regression 6a include a single observation of all wines observed as an originally chosen wine or an alternative wine in the study, omitting duplicates. In regressions 6b, 6c, and 6d, we dropped 26 observations due to participant error in bidding.
†Omitted reference categories are *Sauvignon Blanc*, *California* appellation, and *Beaulieu Vineyards*.
‡*Age* is defined as the 2009, the year the study took place, minus the vintage of the wine.
§The appellation variable includes all constituent sub-appellations.
¶*Central Coast* includes San Francisco and Santa Cruz area appellations.

consumer WTP estimated to be \$0.61 per year. While variety parameters tended to be similar to estimates in 6a, they had smaller standard errors, resulting in an increase in the number of statistically significant estimates. In addition to *Cabernet Sauvignon*, *Pinot Noir*, *Other Red Varieties*, and *Zinfandel*, *Merlot,* and *Red Blend* were valued significantly more than *Sauvignon Blanc*. *Pinot Noir* was still the most highly valued variety, with a premium of \$4.72. Only two variables—*Other White Varieties*, and *White Blend*—had parameter estimates differing from the marginal attribute price model by more than \$0.35.

Appellation WTP estimates tended to be smaller than marginal price estimates. The estimated WTP for *Napa Valley*, for instance, was only \$6.54 (compared to a marginal attribute price of \$9.87). Appellation estimates were lower by at least \$1.97 when examining WTP with the exception of *Monterey* and *San Luis Obispo*. The WTP estimate for *Monterey* was only \$0.84 lower than the price estimate, and WTP for *San Luis Obispo* decreased \$1.05 from the marginal price estimate.[7]

Multiple factors may lead to smaller parameter estimates for appellation from WTP than from market prices. Consumers selecting higher-priced wines—who therefore more likely saw *Napa Valley* wines as alternatives—may have preferred their original choices more than consumers with lower-priced original wines, and would have submitted relatively lower WTP bids for the alternative wines compared to their market prices. Additionally, because the price regression included one observation of each of the original or alternative wines in the experiment, wines were not weighted representatively. A low-priced wine chosen by five participants and a high-priced wine appearing once were given equal weight in the sample used to estimate marginal attribute pricing.

More winery names became statistically significant with WTP as the dependent variable, due in part to decreased standard errors. We find ten winery coefficients statistically different from *Beaulieu* at standard significance levels. However, unlike appellation and variety variables, winery estimates changed markedly with WTP as dependent variable. Consumers did not value *Rosenblum*, the only winery with a positive statistically significant marginal price estimate, significantly more than *Beaulieu Vineyards*, while the WTP estimates for *Husch* and *Sterling* were positive and significant at \$3.38 and \$2.16, respectively.[8]

Finally, we included a dummy variable for each participant's original wine choice. The coefficient on this variable is highly significant and positive, with an estimate implying that participants were willing to pay \$2.40 more for the original wine than the alternatives. A couple factors may contribute to the size of this estimate. We would expect participants to value wines they selected more than a random wine from the same price range. Additionally, the difference in choice setting (e.g., lack of wine labels) may have led to lower bids for alternatives.

6.3. Consumer WTP: wine attributes and consumer characteristics

Next we introduced data on participant characteristics into the analysis. A likelihood ratio test of the model with consumer characteristics versus the restricted model rejects the restricted model ($\chi^2(9) = 168.57, P < 0.0001$). WTP for *WineAge* is now

[7] The data set used to estimate the marginal attribute prices differed from the data set used to estimate the WTP regressions, making direct testing of the equivalence of parameter estimates infeasible. Using seemingly unrelated regression to generate covariance estimates between models—recognizing that the error terms are likely to be correlated—we ran the price and WTP regressions using both the smaller data set used for the price regression and the full data set used for the WTP regressions. None of the grape variety parameters differed significantly, and only the parameter estimates for *Central Valley* ($P < 0.05$), *Napa Valley* ($P < 0.01$) and *Napa and Sonoma Sub-Appellations* ($P < 0.01$) differed significantly between the models. These results were consistent for both data sets.

[8] The parameter estimates on these variables were not significantly different across the marginal price and WTP models.

estimated to be \$0.56 per year, down \$0.05 from the previous model; this change is not statistically significant. Estimates of WTP for *Chardonnay* and *Other White Varieties* become statistically significant once consumer characteristics are added to the analysis. Estimates of WTP for appellations uniformly decrease, though only the parameter estimate for *Napa Valley* changed significantly with the addition of consumer characteristics ($P = 0.04$). With the exception of *Columbia Crest* and *Cycles Gladiator*, the set of statistically significant winery variables did not change, and the changes in parameter estimates for *Columbia Crest* and *Cycles Gladiator* across models were not statistically significant. The indicator variable for a participant's original wine again had a positive statistically significant coefficient and implied a \$2.40 premium for the original wine.

Consumer characteristics with a statistically significant effect on wine valuation were *Price Paid per Bottle*, *Class*, and *Education*. The parameter estimate on *Price Paid per Bottle* was 0.14, indicating that a one-dollar increase in average price paid per bottle corresponded to an increase in WTP for a 750-mL bottle of wine—for original and alternative bottles—of \$0.14. Participants who had taken a wine class were willing to pay \$1.26 more per bottle than other participants. *Literature*, a variable representing whether participants read books or magazines on wine, is neither statistically significant nor highly correlated with *Class*. The correlation coefficient between *Class* and *Literature* was 0.29. It may be that the relatively small sample of rated wines at the supermarket led to insignificant WTP estimates for *Literature* if most participants who reported reading wine literature used wine rating magazines to identify highly rated bottles. Finally, more education reduced WTP for wine, with an additional year of school decreasing WTP per bottle by \$0.41.

6.4. *Consumer WTP: wine attributes and fixed effects*

Finally, we introduce individual-specific fixed effects, accounting for participant sorting into a price location and omitted consumer characteristics, into the analysis. These results provide the cleanest estimate of aggregate WTP for wine attributes. Incorporating fixed effects systematically changes WTP estimates, providing striking evidence of the importance of accounting for sorting and unobserved variables. A likelihood ratio test of the model with fixed effects versus the restricted model rejects the restricted model ($\chi^2(249) = 1928.15$, $P < 0.0001$).

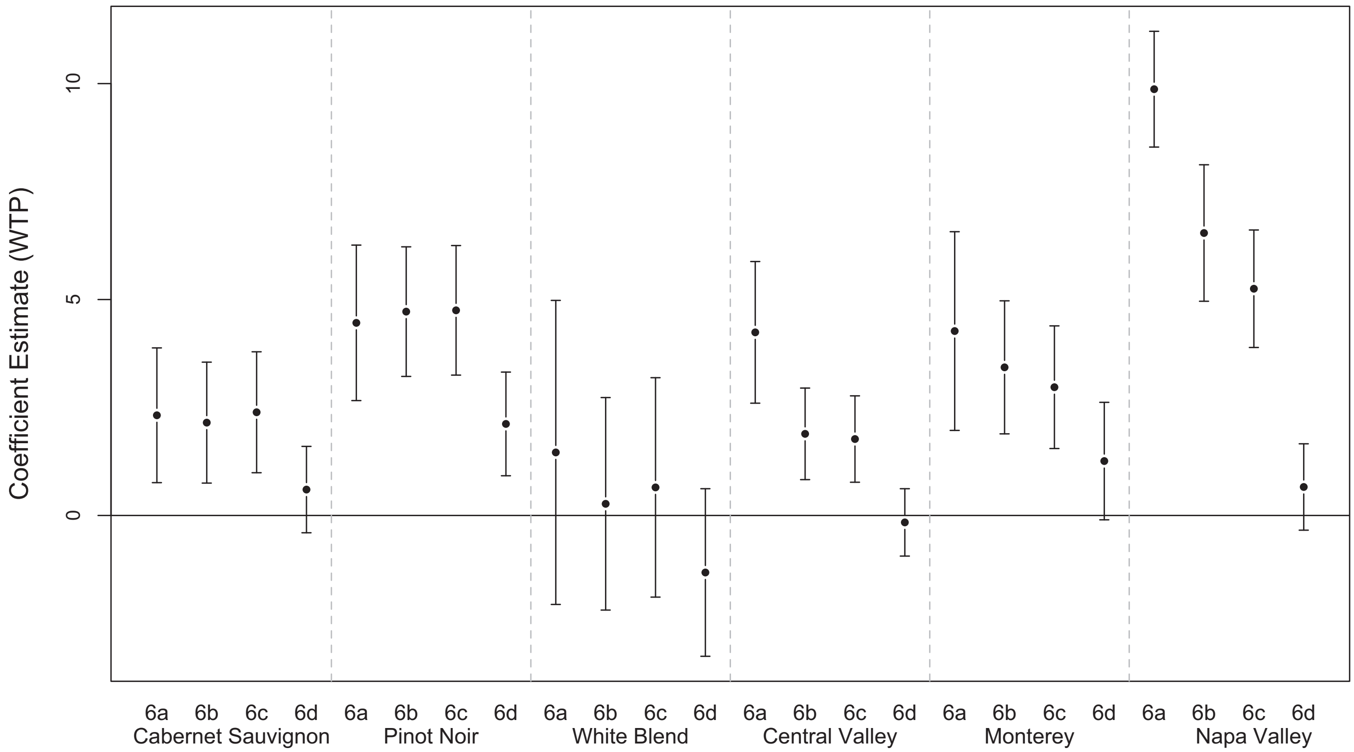
WineAge falls from \$0.56 to \$0.09 per extra year of age, which is a statistically significant difference ($P < 0.01$). A possible explanation is that *WineAge* is correlated with cost of production—and, therefore, market price (Costanigro et al., 2007)—and fixed effects eliminate the relationship between *WineAge* and participants' location in the price dimension. Consumer WTP for grape variety changes once fixed effects are incorporated into the analysis. While consumers were willing to pay more for all included grape varieties than for *Sauvignon Blanc* previously, only *Pinot Noir* is valued more at a statistically significant level, and *Red Blend* and *White Blend* have negative—though insignificant—estimates when fixed effects are included. All of the variety parameters differ significantly between the model with fixed effects and the consumer characteristics model except for *Pinot Grigio*, *Other White*, and *White Blend*.

Changes also occur among appellation coefficients when fixed effects are introduced. All appellation WTP estimates decrease. For instance, the estimate of WTP for *Napa Valley*, which was \$4.59 and statistically significant in the previous regression, falls to \$0.66 when we introduce fixed effects ($P < 0.001$). Further, the range of estimated WTP for appellations shrinks, decreasing from \$5.25 when consumer characteristics were included to \$1.42 (WTP for *Monterey* minus WTP for *Central Valley*) with fixed effects. Of the nine appellations valued more than *California* at significant levels in the previous analysis, none is significant at standard levels once we include fixed effects in the model. Six appellation parameters differed significantly between the fixed effects and consumer characteristics models. Only *Monterey*, *Other Central Coast*, *Other North Coast*, and *Santa Barbara* did not change significantly. We find similar results for winery name. Only one parameter estimate is statistically significant—*Castle Rock*, with a coefficient estimate of –1.84—in the fixed effects model, though the change in parameter estimate between the Fixed Effect and Consumer Characteristics models is not significant. The indicator variable for the participants' original wines continues to be highly significant, increasing slightly to \$2.54.

Figure 2 illustrates changes in parameter estimates—with 95% confidence intervals—across the four models, highlighting estimates for varieties—*Cabernet Sauvignon*, *Pinot Noir*, and *White Blend*—and appellations—*Central Valley*, *Monterey County*, and *Napa Valley*. The estimates of variety valuation differ little among 6a, 6b, and 6c, but decrease in 6d. The valuation estimates for appellation, on the other hand, decrease in value with every model: when the dependent variable changes from shelf price to WTP, and with the addition of individual-specific characteristics and fixed effects.

An interpretation of the sum of our findings is that much of the difference in parameter estimates in the marginal attribute price regression—and even the first two WTP models—reflect correlations between market prices and wine attributes, as well as consumer sorting. The use of WTP data as the dependent variable and the addition of consumer characteristics leads to WTP estimates for certain appellations that are significantly lower than their estimated marginal prices. With the inclusion of fixed effects, we examine intra-individual differences in WTP for wine attributes, eliminating the correlation between attributes and the price segments consumers sort into.

While many of the attribute estimates decrease with the introduction of fixed effects, *Pinot Noir* remains highly valued, and appellations such as *Monterey*, *Napa and Sonoma Sub-appellations*, and *San Luis Obispo* are marginally significant. Once participants have chosen a wine in a certain price



Source: Regression parameter estimates from Table 6.

Fig. 2. Estimated WTP from regressions 6a, 6b, 6c, and 6d for selected varieties (Cabernet Sauvignon, Pinot Noir, and White Blend) and appellations (Central Valley, Monterey, and Napa Valley) with 95% confidence intervals. The regressions were based on 877 shelf prices (regression 6a) and 1,724 valuation observations (regressions 6b–6d). Note that the confidence intervals are calculated with reference to the omitted variables (*Sauvignon Blanc* for variety variables and *California* for appellation variables) and do not permit direct comparison across models.

segment of the market, appellation seems not to affect WTP as much as grape variety does. Our results support recent findings in other contexts, such as Black (1999), Bayer et al. (2007), and Dubois and Nauges (2010), who show that more precise controls for unobserved variables dampen estimates of valuation for quality-related attributes like appellation.

7. Conclusions

We used a field experiment to generate a unique data set on consumer WTP for attributes of a differentiated product. Using participants' uninfluenced original choice of a wine to address sorting, participants valued alternative wines randomly drawn from the same market segment. The data allow us to examine the effect on valuation estimates of implementing greater control over the data, culminating in a fixed effects model.

The estimates of marginal attribute values derived from the various econometric specifications tell different stories about the value of wine attributes. When we use shelf prices as the dependent variable, the range of valuation estimates for appellations (the \$9.87 separating *Napa Valley* and *California*) is more than twice that of the range of estimated values for variety (\$4.52). The reverse holds when the full suite of controls is implemented in the fixed effects model. Here, the range of appellation parameters (\$1.42) is less than half of the range of estimated variety parameters (\$3.44), indicating that individuals have stronger preferences among grape varieties than appellations when we account for consumer sorting into market price segments.

The differences in parameter estimates between the hedonic analysis and the regressions using WTP and consumer-specific data show that the forces we address significantly affect estimates of WTP. This is particularly true for appellations. The results suggest that the high values of certain appellations estimated in other research may be attributable to consumer sorting on unobserved quality attributes or differences in production costs. Here, marginal WTP for *Napa Valley* is not greater than other appellations, implying that other inputs or signaling devices can substitute for the reputation that appellations communicate. In the price segment we study, the American wine market is highly competitive, and consumers appear to have a wider range of preferences for wine varieties than appellations. These findings may not hold at higher price levels, where wines from more precisely defined appellations are thought to possess characteristic sensory qualities unique to each area; for instance, Napa Valley sub-appellations are thought to provide different sensory expressions of the cabernet sauvignon grape (Heimoff, 2013).

In this article, we demonstrate a method to generate data on valuation and consumer characteristics that allow for estimation of WTP parameters rather than marginal implicit prices and that permit us to control for consumer characteristics. The resulting analyses show that estimates of attribute valuation differ significantly when these data—typically unavailable—are used. While there are clear correlations between wine appellations and prices in the market—and there are certainly consumers willing to pay the market prices for those wines—appellations may function more as a quality signal than as a fundamental component of consumer demand in this price range.

Our findings indicate that there is more room for producers operating in lesser-known wine-producing areas to be competitive in the price range we examined than market data alone would imply. Market prices indicate a large premium for Napa Valley and sub-appellations of Napa Valley and Sonoma County. While our data do not identify the elements that drove participants to choose the original bottle of wine they selected, it is clear that once they made that decision changes in appellation had little impact on participants' WTP. This suggests that winemakers may be able to employ inputs other than appellation to signal quality, providing access to higher value market segments.

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