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A Methodology for Evaluating How Product Characteristics Impact Choice in Retail Settings with Many Zero Observations: An Application to Restaurant Wine Purchase

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An approach is developed to examine the impact of product characteristics on choice using a quantity-dependent hedonic model with retail panel data. Since panel data for individual products from retail settings can include a large number of zero sales, a modification of the zero-inflated Poisson (ZIP) regression model is proposed for estimation. Results for this model compare favorably to results for alternative hurdle and negative binomial models. An application of this methodology to restaurant wine sales produces useful results regarding sensory characteristics, price, and origin-varietal information.

Key words: hedonic, restaurant, sensory, wine, zero-inflated Poisson (ZIP)

Introduction

As competition for food markets becomes more intense and food producers look for ways to encourage consumer preference for their products, it is useful to develop methods for understanding the impact of product characteristics on consumer choice. Experimental work and hedonic price analysis both provide some information on consumer choice but cannot address all questions of interest. Such approaches can also produce results which conflict with observed choice behavior in actual retail situations. In experimental work, this can occur because subjects pay closer attention to the object of a study than they would in actual retail settings, thus inflating apparent preference effects. On the other hand, typical applications of hedonic models may have more to do with production costs than with consumer valuation. Further, both approaches tend to limit the descriptive factors that can be examined. The complementary approach of modeling observed retail sales data therefore has the potential to greatly add to our understanding. In this study, a methodology is developed which allows examination of the impact from descriptive information on product choice using a hedonic model with data from a restaurant or retail store.

There are a number of analytical and methodological considerations when using such retail data. First, since price is generally exogenous in these settings, a hedonic quantity

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model rather than price model is appropriate. Second, labeling, signage, and promotional activities may all be relevant when preparing for data collection. Third, although panel data allow all these pieces of information to be used in examining demand, many zero quantity observations can result. Finally, product choice data can give rise to many forms of response variable, including continuous and categorical data. Here, however, the focus is count data, and so the econometric model selected for analysis must also handle this feature.

These considerations are explored by examining the impact of sensory and other characteristics on wine selection in a restaurant setting. Because the data have many zero observations, a modification of the zero-inflated Poisson (ZIP) model is developed for estimation, and found to provide a better fit to the data than alternatives such as hurdle and negative binomial models.

The next two sections provide background on the theoretical underpinnings of a hedonic quantity approach and a review of economic literature relevant to wine characteristics and quality. This is followed by a discussion of the motivation for modeling wine demand at the restaurant level, and consideration of those factors that can be examined more fully at this level of aggregation. The next section provides a description of the methods and data for this type of analysis and gives details regarding the specific data used. In the remaining sections, the empirical model, results, and conclusions are presented.

Theoretical Model

A principal feature of the approach used here is the underlying quantity-dependent hedonic model. The hedonic approach was originally designed with price as the dependent variable, and assumed that price contains the information inherent in consumer valuation of product attributes. Rosen (1974) extended hedonic price theory by determining market equilibrium conditions for valid estimation. Nerlove (1995), as well as Brown and Rosen (1982), identified additional problems with this approach and further limited the appropriate applications for hedonic price models. Nerlove, noting that prices are frequently exogenous to a subset of buyers, developed a model in which the hedonic index is quantity sold. Under his development, any commodity can be described by specific attributes ($\mathbf{Z} = Z_1, \ldots, Z_n$), and this attribute bundle then influences the utility provided by the commodity, $U[V[\mathbf{A}(\mathbf{Z}), \mathbf{Q}(\mathbf{Z})], \mathbf{X}]$, where $\mathbf{A}(\mathbf{Z})$ is a vector of quality valuations for those attributes, $\mathbf{Q}(\mathbf{Z})$ is a vector of quantities purchased from the available varieties, $\mathbf{X}$ is a vector of the quantities of other goods purchased, and V is a function of the quantities purchased of the wines and the valuation of their attributes.

If the utility function is separable and homothetic between V and $\mathbf{X}$, and consumers take prices, $p(Z)$, as given, then they maximize utility by their choices given those prices and their own characteristics, $\mathbf{Y}$, such as income. Then a spectrum of demand across products is given by $\mathbf{Q}(\mathbf{Z}) = F[p(Z), \mathbf{Y} \mid a(Z)]$, where the quality index $\mathbf{A}(\mathbf{Z})$ can be represented by a common function of the elements of $\mathbf{Z}$, $a(Z)$. This important consideration is appropriate only under specific circumstances. For example, in a limited market where consumer actions do not affect price, and if supply is essentially unlimited and unaffected by changes in consumer demand, a quantity-dependent hedonic approach with price as an exogenous variable becomes appropriate. This scenario fits the general retail situation in which products are storable, prices are fixed at the sales level, and consumers make purchases based upon the prices and other information available.

Further, given Nerlove's framework, the attributes can be valued based on the ratio of the parameters derived from a regression with quantity as the dependent variable: $(\partial F/\partial Z)/(\partial F/\partial P) = \partial P/\partial Z$. If this is considered a linear relationship, then the amount by which the attribute shifts the quantity measure can be converted into a price shift by assessing the price shift caused by an equal quantity shift.

Literature Review

A number of studies into wine quality have used hedonic analysis, but relatively few studies in the economic literature have relied on a hedonic price model. One example, Oczkowski (1994), employs a hedonic price model to evaluate characteristics influencing Australian wine prices; vintage and a vintage-varietal interaction partly accounted for the endogeneity of quantity supplied.

Several studies have analyzed reputation and expert rankings (Landon and Smith, 1998; Combris, Lecocq, and Visser, 1997, 2000; Schamel, 2000). Schamel, and Landon and Smith, use *Wine Spectator* ratings (a popular source of wine information) as measures of quality. Schamel estimates a hedonic price model across multiple countries and origin locations. Landon and Smith limit their application to one region and two vintages to examine how quality and reputation impact price in a jointly estimated model of price and quality. They found that past quality appears to be more important than current quality. Neither study incorporates specific sensory descriptions of wine.

Using expert panel jury ratings, Combris, Lecocq, and Visser (1997, 2000) evaluate the importance of sensory measures in separate analyses of Bordeaux and Burgundy wine. Because price is not a factor in the jury rating (whereas it is in the consumer purchasing decision), they were unable to convert the jury rating characteristics into a price premium, as done by Nerlove (1995). However, the authors do separately test a hedonic price equation to examine the impact of the jury-rated characteristics on market price. Only two of the jury panel characteristics were significant in the price equation: whether the wine (flavor) was concentrated, and whether the wine needed extended storage (often associated with wines that develop over time).

In the Combris, Lecocq, and Visser hedonic price equations, panel ranking of the wine was also used as an explanatory variable. Though prices were set before the jury ranking, it is possible the winemaker would have assessed wine quality with expertise similar to that of the panel. In their 1997 analysis of Bordeaux, Combris, Lecocq, and Visser provide two possible explanations for their finding of fewer significant sensory characteristics in the price equation than in the jury rankings. First, consumers do not have perfect information for all characteristics and are thus much more likely to use the "objective" characteristics found on the label (origin, maker, vintage) to make choices. Alternatively, they suggest that consumers are heterogeneous and may have negative and positive reactions to the same characteristics. Consequently, characteristic effects on choice or price are diluted when averaged across consumers.

In contrast, we use a hedonic quantity model to evaluate the impact of objective characteristics, sensory descriptors, and price on wine choice. In common with Nerlove, the hedonic index is quantity sold, but in a particular restaurant rather than across a nation. The primary difference between this and previous wine choice studies is our utilization of a quantity-dependent model. This approach allows the results to provide unique insights into consumer valuation.

Wine Sales in Restaurants

Wine is particularly well suited to the approach developed in this study. Restaurant sales data allow the influence of sensory descriptions, origin-varietal information, and technical measures all to be examined. In restaurants that offer high-quality wine, customers are provided with a wine list from which to consider their selection. A common practice is to sort the wines into white, red, and sparkling wines, and then group by varietal and/or origin within each subset. In many instances, restaurants supply a description of the sensory qualities of the wine along with the brand, vintage, origin, and price.

In comparison to wine purchases in retail stores, information availability differs for buyers in restaurants in two important ways. First, the restaurant wine list information on sensory characteristics allows immediate comparison for each wine,[1] and second, the customer rarely sees the bottle until it is being opened. Sensory information usually includes aroma, flavors, and sometimes "mouth feel" (dry, tannic, smooth). Typical descriptions for aroma and taste include different types of fruits (berry, lemon), or flowers (apple, rose). Food associations are not limited to fruits and flowers. Terms such as herbal, honey, and chocolate are also sometimes associated with wines. Not all descriptors are immediately attractive or meaningful to unsophisticated wine buyers. For example, for some wine varietals, a description of a "flinty" flavor or an aroma of "saddle leather" is considered complementary. There are also numerous, widely accepted terms for mouth feel, concentration, or texture that are not associated with a taste or smell, such as big, creamy, or heavy. A widely distributed wine aroma wheel is broadly accepted as definitive for researchers looking at aroma (Noble et al., 1987), and it is generally a good source of taste attributes as well.

Restaurant wine stewards or sommeliers generally provide sensory descriptions based on personal tasting, though accuracy may be questionable in restaurants which lack sufficiently trained or experienced employees. Some winemakers include descriptions with their wine shipments (Hochstein, 1994). While research into the impact of sensory descriptions on choice is limited, their broad use and inclusion in critical wine evaluations from *The Wine Spectator* and *The Wine Advocate* suggest a perceived importance. Charters, Lockshin, and Unwin (1999) found that 57% of a sample of 56 Australian wine consumers claimed to read the back label of wine bottles, and these consumers reported the most useful information was the "simple descriptions of the tastes or smells."

The Data

When using restaurant data for this type of study, the quantities sold and menu information are the principal requirements. In contrast, if data from a retail store were to be used, then the variety of products might require a laborious recording of label features and signage, as well as sensory information and other descriptions on packages, including nutritional information in some cases. For fresh products, a method of visual quality evaluation would be necessary. Though restaurants may be less likely to have convenient computerized sales records, the limited product information available to the consumer

[1] This is not always the case; often a list of wines by the glass does not include such information, though the information may be sought from the waiter and can often be found in the "by the bottle" section of the wine list.

has some advantages from the perspective of modeling. To encourage participation, a willingness to provide feedback to the retailer on findings is recommended, while a further important consideration is to minimize the efforts of the proprietors and their staff. To enhance the accuracy and quality of collected data, researchers could offer to design a recording system for the restaurant, perhaps in computer form.

The wine data for our analysis were collected between the end of April and the beginning of September 1998, a 19-week period. The selected restaurant has a number of desirable characteristics: it offers a fairly wide selection of wines, but not so wide as to discourage careful consumer examination of the list; the wines offered range from less expensive to premium reserve wines; it offers wines from a variety of origins; and it provides a detailed wine menu for its customers. Daily wine disappearances were summed to obtain weekly quantities in whole numbers of bottles. Many retail environments make product or price transitions on a weekly basis, and weekly observations therefore allow characteristic and price transitions to register. In this data set, one wine was replaced with an alternative selection over the study period.

The menu was the primary tool used by customers[2] to choose among the available wines. For most wines, the menu contained its full name, origin, grape varietal, vintage, and price. In addition, certain wines were set aside in sections for reserve wines, wines sold by the glass, and nonalcoholic wines. The experienced wine steward provided a concise list of the sensory characteristics of each wine based on his tasting. The first page of the menu contained a listing of wines by the glass, followed by two pages which included nonalcoholic wines, a single white Zinfandel, and three Rieslings. The next two (facing) pages were for Chardonnay, with the following two pages devoted to other regional whites (California, Oregon, and Washington). These pages were followed by three sets of facing pages for the domestic reds, grouped as Pinot Noir, Cabernet Sauvignon, and other regional reds (same states). The next four pages were for imported wines, two for whites and two for reds. Sparkling wine, port, and sherry followed on the two succeeding pages, and the reserve list wines (all red) appeared on the final two facing pages. When a grouping consisted of two pages, they faced each other, thus allowing offerings to be viewed together. Varietal information was included for only a few imported wines since most were blended. Nonalcoholic and sparkling wines were not included in the analysis because the decision to drink these particular types of wine is assumed to exclude consideration of other wines.

Red and white wines usually have different sensory characteristics, their prices have different ranges, and they are selected to go with different foods. Red wines are most often selected when eating red meats or pasta with red sauce, while white wines are drunk with other pasta dishes, fish, and chicken. Many of the sensory characteristics are specific to red or white wines, and thus would not have been part of the spectrum of possible characteristics across all wines. For these reasons, red and white selection were modeled separately.

Origin and varietal information can either be treated independently or modeled as a pair. With sufficient variability in the data, it might have been possible to evaluate origin and varietal effects separately as well as joint effects for specific combinations. However, many of the specific varietals were from regions where that varietal was recognized for good quality. For example, all but one of the Cabernet Sauvignon selections

[2] Certainly, the wait staff would sometimes be asked for information.

and all of the Zinfandels were from California. Thus, although these could be treated separately, it would be inaccurate to treat a parameter estimate for Zinfandel as a "Zinfandel effect" across all origins. Therefore, our model treats origins and varietals as pairs, although data limitations required some wines to be aggregated as more general "others."

For red wines in this analysis, the breakdown designations are California Cabernet Sauvignon, California Zinfandel, Oregon Pinot Noir, Other California Reds,[3] Other Northwest Reds,[4] French Reds, and Italian Reds, with California Merlot as the base wine. For white wines, the base is California Chardonnay, with Oregon Chardonnay, Oregon Pinot Gris, Other California Whites,[5] Other Northwest Whites,[6] and French Whites providing the other categories. Note that non-domestic red and white wines only indicate origin, not variety. Oregon wines are strongly represented because the study restaurant is located in Oregon, Oregon Pinot Noir has an internationally recognized reputation, and Pinot Gris is considered the best Oregon white. Oregon Chardonnay provides an opportunity to contrast with the better-known California source.

For experienced wine enthusiasts, the combination of vintage year, varietal, and origin provides information about the grape quality of a specific wine. According to the study restaurant's wine steward, about 5% of the restaurant's clientele might have some knowledge regarding a good or bad vintage. While model and data limits precluded accurate testing of vintage impacts, it is unlikely to be relevant for this population of consumers.

Sensory descriptors are derived from the wine list, with some related sensory terms combined (provided in parentheses in the following discussion). Those common to red and white wines in the menu included body (full, big, lots of), finish (long or smooth, etc.), oak, spicy (included some specific terms), and tannic (medium, firm, plenty of). Those descriptors specific to reds were vanilla, currant (black or red), berry (black, Marion, raspberry), cherry, and chocolate flavors, while those specific to whites included creamy, buttery, dry, honey, melon, citrus (included lemon or grapefruit), tree fruit (apple, peach, or pear), and tropical fruit. The restaurant wine steward does feel that customers respond to the sensory characteristics in the wine list, but he cannot say to what degree.

The sensory descriptors identified above are represented by dummy indicator variables in the model. Other descriptors applied to only a few wines, and so were excluded from consideration. Interaction terms are not included in the model due to data limitations, though the interaction, for example, of full bodied and fruity characteristics might contribute more than the sum of their individual parts. Such an approach would require more sensory characteristics to be combined for tractability, thus losing out on the information more specific to particular characteristics.

Price is by the bottle as listed on the menu, with the exception of wines available by the glass, which are priced by the rule[7] given by the wine steward; these match the prices for house wines in other parts of the menu. To examine the hypothesis that customers tend to avoid buying the lowest priced offering in any set of wines, a dummy

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[3] "Other California Reds" include a Syrah, Petit Syrah, and varietal blend.

[4] "Other Northwest Reds" include Washington or Oregon Cabernets and Merlots.

[5] "Other California Whites" include Fume Blanc, Gewurtztraminer, White Zinfandel, and a Sauvignon Blanc/Semillon blend.

[6] "Other Northwest Whites" include Muller Thurgau, Chenin Blanc, Gewurtztraminer, and Riesling.

[7] Whole bottle price is four times the per glass price less $1.

indicator variable (*Low Price*) was added for wines with the lowest price in a grouping from the wine list as described above. Also, wines sold by the glass were designated using a dummy indicator variable (*Glass*).

In summary, the data consist of the following variables for 76 wines (47 red, 29 white):

- *Quantity* sold in each of 19 weeks (dependent variable).
- *Price*, *Low Price*, and *Glass*.
- Origin-Varietal, consisting of: (*a*) seven variables for red (*California-Cabernet Sauvignon*, *California-Zinfandel*, *Oregon-Pinot Noir*, *California-Other*, *Northwest-Other*, *French Red*, and *Italian Red*) relative to the base red wine of California-Merlot; and (*b*) five variables for white (*Oregon-Chardonnay*, *Oregon-Pinot Gris*, *California-Other*, *Northwest-Other*, and *French White*) relative to the base white wine of California-Chardonnay. Table 1 provides statistics on the distribution of wine available and sold for the origin-varietal pairings used in the analysis.
- Five sensory characteristics common to both red and white wines: *Body*, *Finish*, *Oak*, *Rich*, and *Spices*.
- Fourteen sensory characteristics unique to red (six) and white (eight) wines: *Currant*, *Berry*, *Cherry*, *Chocolate*, *Tannic*, and *Vanilla* for red wine; and *Buttery*, *Creamy*, *Dry*, *Honey*, *Melon*, *Citrus*, *Tree Fruit*, and *Tropical Fruit* for white wine. Table 2 reports statistics on the frequency of the characteristics in the available wines.

The dependent variable, *Quantity*, is a nonnegative, integer-valued count of the number of bottles of a particular wine sold in one week; its frequency distribution is highly positively skewed with a large mode at zero. Only one of the explanatory variables, *Price*, is continuous. Table 3 presents summary statistics on red and white wine prices.

Empirical Model

In common with much retail data, particularly for restaurants or high-valued products, our wine data contain many zero quantity sales. The large number of zeros suggests the data are over-dispersed relative to the Poisson distribution, the usual discrete probability distribution used for count data. Therefore, standard Poisson regression models are not suited for our purposes. To address this problem, a modification of Lambert's (1992) zero-inflated Poisson (ZIP) regression model is used. The ZIP model is of relatively recent adoption in economic research, with the first published paper in the economics literature to use the zero-inflated Poisson model in 1996 (Bohara and Krieg). A number of studies using the ZIP model (Bohara and Krieg, 1996; Cameron and Englin, 1997; Tomlin, 2000) compare it favorably to alternative models. Hurdle models (Mullahy, 1986) have been used more often in the economics literature, particularly for food demand analysis (Angulo, Gil, and Gracia, 2001; Burton, Tomlinson, and Young, 1994; Manrique and Jensen, 2001; Mihalopoulos and Demoussis, 2001; Newman, Henchion, and Matthews, 2001; Yen and Huang, 1996). The primary difference between the ZIP and the hurdle approach is how zero observations are treated in the model (Melkersson, 1999).

Table 1. Bottles Sold and Availability of Wine by Origin-Varietal Information

Red Wines	Sold	Available	White Wines	Sold	Available
California Merlot	231	5	California Chardonnay	240	6
California Cabernet	195	12	Oregon Chardonnay	114	6
California Zinfandel	38	4	Oregon Pinot Gris	101	2
Oregon Pinot Noir	127	9	California Other White	127	4
California Other Red	4	3	Northwest Other White	174	5
Northwest Other Red	23	4	French White	6	6
French Red	26	7			
Italian Red	5	2			
Total Red:	**649**	**46**	**Total White:**	**762**	**29**

Table 2. Percentage and Number of Wines Available with Sensory Characteristic (observed over the study period)

<— Red Wines —>			<— White Wines —>		
Description	%	Number	Description	%	Number
Glass	8.7	4	Glass	17.2	5
Low Price	6.5	3	Low Price	13.8	4
Common Characteristics:			**Common Characteristics:**		
Finish	34.2	16	Finish	10.3	3
Oak	31.0	14	Oak	10.3	3
Spices	21.7	10	Spices	20.7	6
Body	58.7	27	Body	37.9	11
Rich	34.8	16	Rich	31.0	9
Characteristics Specific to Red Wines:			**Characteristics Specific to White Wines:**		
Tannic	58.7	27	Buttery	20.7	6
Vanilla	16.8	8	Creamy	10.3	3
Currant	27.7	13	Dry	27.6	8
Berry	32.0	15	Honey	13.8	4
Cherry	39.1	18	Melon	24.1	7
Chocolate	8.7	4	Citrus	20.7	6
			Tree Fruit	20.7	6
			Tropical Fruit	24.1	7

Table 3. Summary Statistics for Price of Red and White Wines

	Price Statistics ($/bottle)			
Description	Mean	Std. Dev.	Minimum	Maximum
Price Red Wine	45.0	25.5	19	145
Price White Wine	27.0	9.9	13	48

In this application, Q_i denotes the number of bottles of wine sold in a week, where there are 76 different wines sold over a 19-week period, so that $i = 1, ..., n = 1{,}425$ (one of the red wines replaced another during the study period). Ordinarily, count data such as these would be modeled using log-linear Poisson regression, with the (log) Poisson means dependent on characteristics associated with each wine. However, these data exhibit over-dispersion, in this case with more zero counts than a Poisson model allows. For example, of the 1,425 observations, 1,000 (70.2%) were zero (i.e., no bottles of a particular wine sold that week), whereas a log-linear Poisson regression model predicts only 67.8% zeros. A ZIP model, as described below, specifically allows for this over-dispersion, and predicts 70.5% zeros.

The traditional way in which a ZIP model allows for over-dispersion is to assume that the counts follow a mixture distribution: Poisson (μ_i) with probability p_i, or identically zero with probability $1 - p_i$, where μ_i is the Poisson mean. The Poisson means are modeled as a function of the wine characteristics, and the zero probabilities either can be completely stochastic or can also be modeled as a function of the wine characteristics. We modify this setup in light of the fact that one of the wine characteristics—*Glass*—almost guarantees nonzero (positive) sales. There were nine wines available by the glass, and of the 171 weekly counts for these wines, only nine were zeros. Such wines were modeled as Poisson (μ_i). Other (non-glass) wines followed the usual ZIP model. Thus, the count probabilities are as follows:

$$\Pr(Q_i = 0) = \exp(-\mu_i)I(Glass = 1) + (1 - p_i + p_i\exp(-\mu_i))I(Glass = 0), \tag{1}$$

$$\Pr(Q_i = q) = (\exp(-\mu_i)\mu_i^q/q!)I(Glass = 1) + (p_i\exp(-\mu_i)\mu_i^q/q!)I(Glass = 0), \quad \{q = 1, 2, \dots\}. \tag{2}$$

Link functions relating $\boldsymbol{\mu} = (\mu_1, ..., \mu_n)$ and $\mathbf{p} = (p_1, ..., p_n)$ to wine characteristics can be written as:

$$\log(\boldsymbol{\mu}) = \mathbf{X}_1\beta, \tag{3}$$

$$\text{logit}(\mathbf{p}) = \log(\mathbf{p}/(1 - \mathbf{p})) = \mathbf{X}_2\eta, \tag{4}$$

where $\mathbf{X}_1$ and $\mathbf{X}_2$ are covariate matrices with columns corresponding to wine characteristics. The covariate matrices can contain covariates in common, and usually $\mathbf{X}_2$ contains a subset of the covariates in $\mathbf{X}_1$. For our application, $\mathbf{X}_1$ consists of the 44 variables described above, while we use an intercept term, *Price*, and *Low Price* for $\mathbf{X}_2$. These latter choices were based on an initial logistic regression analysis for zero versus nonzero. After *Glass* (which was clearly the most important discriminator), *Price* was the next most useful discriminator, followed by *Low Price*. Incorporating further covariates in $\mathbf{X}_2$ made a negligible improvement in model fit.

Model Estimation

ZIP models can be fit from a classical (frequentist) perspective with, for example, the TRAJ procedure in SAS (Jones, Nagin, and Roeder, 2001). However, the SAS procedure is restricted to a single covariate in $\mathbf{X}_2$ for modeling the zero probabilities, and cannot easily be adapted to incorporate the adjustment for wines by the glass as described above.

An alternative approach is to put the model into a Bayesian framework. For such a Bayesian approach, prior distributions for β and η must be specified. With small samples this choice can be critical, but with larger samples (such as in this application) the choice is less crucial, since information in the data heavily outweighs information in the prior. Thus, β and η are given uninformative zero-mean normal priors with standard deviations of 10. In other words, the only assumption made before conducting the analysis is that it is implausible for the β and η parameters to be more than about ±20. We used WinBUGS software (Spiegelhalter et al., 2003) to generate posterior samples for β and η. WinBUGS facilitates Bayesian analysis of complex statistical models using Gibbs sampling, a Markov chain Monte Carlo (MCMC) technique.

Model Assessment

We first fit a ZIP model with just a constant and *Price* in $\mathbf{X}_2$. Four chains of 19,750 iterations each for this model produced trace plots with a good degree of mixing, and various MCMC convergence diagnostics indicated convergence. In particular, after discarding 7,750 burn-in samples and thinning to retain every 12th sample to reduce autocorrelation (leaving a total of 4,000 posterior samples), the 0.975 quantiles of the corrected scale reduction factor (Brooks and Gelman, 1998) for the β and η parameters were each 1.2 or less (a rule of thumb commonly used to assess convergence). MCMC samples generally have to be allowed to proceed past an initial burn-in period to reduce any adverse effects from the starting values for the chains, while thinning reduces computer storage requirements when very long runs must be carried out due to high autocorrelation.

To gauge the improvement in fit from accounting for over-dispersion by using a ZIP model, we also fit a standard log-linear Poisson regression model. A hurdle model was tested as well, with the wine counts following a similar mixture distribution to the ZIP model but using the zero-truncated Poisson distribution instead of the regular Poisson distribution. Thus, whereas zero counts under the hurdle specification are all handled with the "identically zero" part of the model, zero counts under the ZIP specification can also arise from the Poisson part of the model.

Finally, an alternative approach for modeling over-dispersed data using random effects is examined. In particular, the standard log-linear Poisson regression model can be generalized so that each observation has its own multiplicative random effect on the Poisson mean. So, rather than restricting these means to be based only on the characteristics of the wines, they can also be adjusted up or down to reflect unexpectedly high or low demand. If these random effects are assumed to follow a gamma distribution with mean one, then, marginally, the wine counts follow a negative binomial distribution.

Table 4 compares the models with respect to minus twice log-likelihood (−2LL) values, Akaike's information criterion (AIC) (Akaike, 1973), Bayesian (or Schwarz's) information criterion (BIC) (Schwarz, 1978), and the deviance information criterion (DIC) (Spiegelhalter et al., 2002). Also included are the predicted probabilities of zero, one, and two or higher counts.

The ZIP model has lower AIC, BIC, and DIC values than the standard Poisson, hurdle, and negative binomial models (indicating a better fit to the data). These latter three models are also less effective than the ZIP model at predicting count probabilities, as can be seen in the last three columns of table 4. The observed proportions of zero, one,

Table 4. Comparison of Models' Goodness-of-Fit Measures

	Fit Measures [a]				Predicted Probabilities (%)		
Model	-2LL	AIC	BIC	DIC	Zero	One	Two+
Standard Poisson	2,489	2,577	2,808	2,573	67.8	16.9	15.3
Zero-Inflated Poisson	2,427	2,519	2,761	2,517	70.5	12.1	17.3
Hurdle	2,496	2,588	2,830	2,576	70.1	14.6	15.3
Negative Binomial	2,469	2,559	2,796	2,557	68.2	16.6	15.2

[a] Fit measures are defined as follows: -2LL = minus twice log-likelihood, AIC = Akaike's information criterion, BIC = Bayesian information criterion, and DIC = deviance information criterion.

and two or higher counts in the data were 70.2%, 12.8%, and 17%, respectively. The standard Poisson model underestimates the number of zeros, overestimates the number of ones, and underestimates higher counts, while the ZIP model estimates these proportions much more accurately (off by not more than 0.7% for counts of zero, one, and two or more). The hurdle and negative binomial models fit the counts better than the standard Poisson model, but less so than the ZIP model.

Adding *Low Price* as a variable in $\mathbf{X}_2$ for the ZIP model provides an almost identical fit to the first ZIP model, at the expense of an added degree of complexity (results not shown). Also, the negative binomial model can be generalized to explicitly account for an inflated number of zeros; again, only a marginal improvement in fit is observed at the expense of an added degree of complexity (results not shown). Finally, at the suggestion of a referee, we also fit a ZIP model without sensory characteristics to assess whether such characteristics accounted for demand above and beyond that which can be explained by origin-varietal, price, and whether the wine is available by the glass. This final model provides a less satisfactory fit, as exemplified, for example, by a DIC value of 2,523—somewhat higher than the corresponding value of 2,517 for the ZIP model with sensory characteristics.

Results

Overall, the first ZIP model (using a constant and *Price* in $\mathbf{X}_2$) appears to offer the most reasonable compromise between parsimony and fitting the sample data well. Summary statistics for the posterior samples of the beta-parameters for this model are presented for red wines in table 5 and white wines in table 6.

The means of the posterior samples provide point estimates for the model parameters, while the standard deviations provide measures of precision. The 95% intervals (calculated using the 2.5th and 97.5th percentiles of the posterior samples) provide an alternative indication of the covariates' effects along with estimation precision. Those 95% intervals that exclude zero are roughly equivalent to classical statistical significance at the $p < 0.05$ level. The column headed "exp(Mean)" indicates the multiplicative impact on the mean quantity sold [e.g., in table 6, the mean quantity sold of a white wine is multiplied by $\exp(0.256) = 1.292$ when that wine has a "buttery" descriptor]. Summary statistics for the posterior samples of the η-parameter for the effect of wine price on the probability of positive demand are: Mean = -0.044, Standard Deviation = 0.008, 95% Interval = (-0.061, -0.028), and exp(Mean) = 0.957. So, for example, a $1 increase in overall price multiplies the odds of positive demand (rather than zero demand) by an estimated 0.957 times, i.e., it is decreased.

Table 5. ZIP Results for Red Wine: Summary Statistics for Posterior Samples of the Beta Parameters

Description	Mean	Std. Dev.	95% Interval[a]		exp(Mean)
Intercept	-0.363	0.471	-1.262	0.546	
Origin-Varietal:					
California Cabernet	-0.454	0.112	-0.672	-0.231	0.635
California Zinfandel	-1.954	0.191	-2.335	-1.595	0.142
Oregon Pinot Noir	-0.825	0.126	-1.079	-0.577	0.438
California Other Red	-2.040	0.667	-3.424	-0.816	0.130
Northwest Other Red	-0.176	0.417	-0.993	0.649	0.839
French Red	-1.674	0.341	-2.360	-1.021	0.187
Italian Red	-1.567	0.597	-2.812	-0.467	0.209
Pricing and Glass:					
Price	0.006	0.007	-0.008	0.019	1.006
Low Price	-0.572	0.484	-1.508	0.358	0.564
Glass	2.549	0.407	1.796	3.339	12.800
Common Sensory Characteristics:					
Body	0.171	0.220	-0.258	0.603	1.186
Finish	0.005	0.241	-0.451	0.480	1.005
Oak	-0.133	0.339	-0.797	0.534	0.876
Rich	-0.267	0.350	-0.944	0.399	0.766
Spices	0.601	0.292	0.040	1.177	1.825
Unique Sensory Characteristics:					
Currant	0.217	0.348	-0.447	0.901	1.242
Berry	0.820	0.338	0.171	1.498	2.270
Cherry	0.725	0.345	0.050	1.410	2.064
Chocolate	0.084	0.431	-0.761	0.943	1.088
Tannic	-0.562	0.240	-1.036	-0.091	0.570
Vanilla	0.116	0.370	-0.615	0.838	1.123

[a] The 95% intervals are calculated using the 2.5th and 97.5th percentiles of the posterior samples.

Origin-Varietal Effects

Posterior samples of the beta-parameters for wine origin-varietals are summarized in panels A and B of figure 1. Varietals are ordered from left to right by their estimated effects (posterior means). The thick black lines represent posterior means, while the dark gray inner bars represent 50% intervals (calculated using the 25th and 75th percentiles of the posterior samples), and the light gray outer bars represent 95% intervals.[8]

Each line/bar represents a red/white intercept + origin-varietal effect. For example, the posterior mean effect size for California Chardonnay is represented by 2.315, while for Oregon Pinot Gris it is 2.315 + -0.838 = 1.477 (figure 1, panel B). Thus, the figure compares log-demand for wines of different origin-varietals, with zero values for all other covariates. This allows easy comparison of origin-varietals within color, including the relevant uncertainty for each origin-varietal indicator as well as the intercept term.

[8] Interval ends will not precisely match those in tables 5 and 6 because the covariance between the estimate of the intercept and other parameter estimates is incorporated in the interval displayed on the figures.

Table 6. ZIP Results for White Wine: Summary Statistics for Posterior Samples of the Beta Parameters

Description	Mean	Std. Dev.	95% Interval[a]		exp(Mean)	Value[b]
Intercept	2.315	0.776	0.804	3.756		
Origin-Varietal:						
Oregon Chardonnay	-1.302	0.173	-1.640	-0.959	0.272	-23.04
Oregon Pinot Gris	-0.838	0.129	-1.097	-0.589	0.433	-15.33
California Other White	-0.912	0.185	-1.268	-0.551	0.402	-15.35
Northwest Other White	-0.866	0.204	-1.258	-0.468	0.421	-13.82
French White	-1.930	0.574	-3.133	-0.872	0.145	-37.48
Pricing and Glass:						
Price	-0.076	0.032	-0.137	-0.012	0.927	
Low Price	-0.965	0.411	-1.792	-0.173	0.381	
Glass	1.489	0.257	1.009	1.995	4.434	
Common Sensory Characteristics:						
Body	-0.659	0.422	-1.482	0.163	0.517	-13.60
Finish	-0.399	0.597	-1.597	0.756	0.671	-8.90
Oak	0.992	0.422	0.171	1.836	2.697	19.33
Rich	0.341	0.399	-0.425	1.128	1.407	3.38
Spices	-0.117	0.375	-0.829	0.623	0.890	-0.38
Unique Sensory Characteristics:						
Buttery	0.256	0.463	-0.674	1.138	1.292	0.57
Creamy	1.182	0.456	0.296	2.069	3.262	20.30
Dry	0.534	0.267	0.011	1.062	1.705	9.96
Honey	-0.040	0.342	-0.702	0.646	0.961	-0.51
Melon	-0.011	0.385	-0.774	0.743	0.989	0.19
Citrus	-0.768	0.401	-1.568	-0.014	0.464	-13.46
Tree Fruit	0.175	0.437	-0.701	1.026	1.191	1.68
Tropical Fruit	-0.099	0.323	-0.714	0.530	0.906	-2.78

[a] The 95% intervals are calculated using the 2.5th and 97.5th percentiles of the posterior samples.
[b] Value is calculated as the mean of the ratio of the beta for characteristic to the beta for price.

Although the values of the red/white intercepts in tables 5 and 6 are essentially arbitrary (since they depend on the dummy variable coding in the data set), the values of the beta-parameter estimates for wine origin-varietals can be unambiguously interpreted relative to the chosen base wines. For example, recoding the *Glass* variable so that zero becomes one and vice versa would change the values of the red and white intercepts, but leave the origin-varietal estimates unchanged.

Within red varieties (figure 1, panel A), California Merlot was most preferred, but Northwest Other Reds, which consisted of three Merlots and one Cabernet, was only marginally less preferred. Because the data were collected at about the height of Merlot's popularity, demand may have shifted since that time. However, Merlot's popularity in the restaurant trade may remain, as it offers an advantage by usually being drinkable earlier than some other reds. Preferences for California Cabernet Sauvignon and Oregon Pinot Noir followed in that order, but were not far behind the Merlots. Italian and French reds were next in preference, with little difference between them. California Zinfandel and California Other Reds were last in preference, and also quite close to each other.

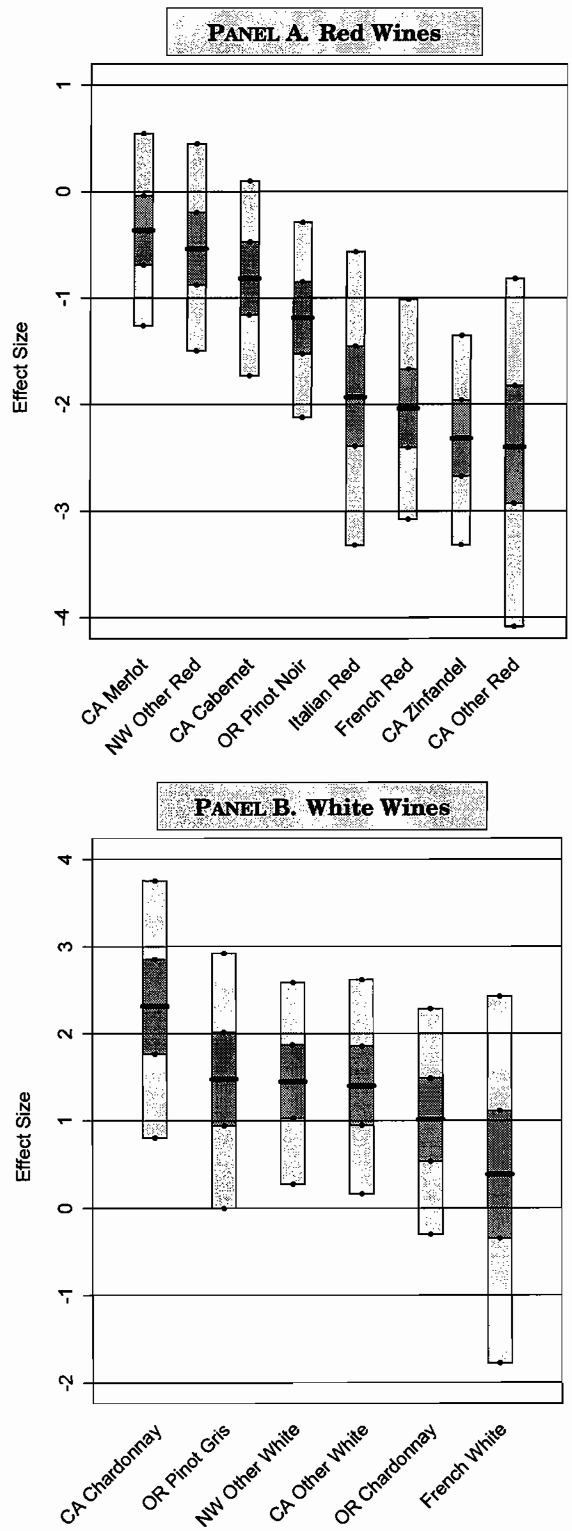

Figure 1. Comparison of effects and precisions for origin-varietal information

For white varieties (figure 1, panel B), all wines trail California Chardonnay, followed first by Oregon Pinot Gris, Northwest Other Whites, and California Other Whites, then Oregon Chardonnay, and finally French Whites.

For both red and white wines, recognition of varietals from U.S. regions where those varietals are known for their quality is observed. Favoritism for local wines does not appear to extend to varieties in which no local prominence has been achieved (such as Oregon Chardonnay). Rather, the local wines of positive reputation, Oregon Pinot Noir for red and Oregon Pinot Gris for white, appear to receive favor.

Nonsensory Characteristic Effects and Price Effects

Wines available by the glass saw increased demand beyond that which could be expected from their relative price and origin-varietal information; this effect was somewhat greater for red wines. The price effect was negative in the first (logit) part of the ZIP model determining the likelihood of a wine being in the nonzero category. However, the effect on count in the second (Poisson) part of the model was negative only for white wines. The price effect on count was solidly negligible for red wines in terms of both absolute magnitude and magnitude relative to its standard deviation. The low price variable effect was negative for both white and red selections, but of greater magnitude for white wines. A possible explanation for this result may be that purchasing more expensive wines can provide a greater sense of satisfaction by allowing the buyer to appear more selective or magnanimous, or at least to avoid giving the opposite impression.

The insensitivity of red wine buyers to price generates a number of possible explanations. Wine drinkers often progress from white to red wines as they learn more about wine and as they develop more sophisticated tastes. Red wine drinkers often have invested additional time in learning more about winemaking and quality sources, allowing them to be more influenced by other features of the wine, such as the winemaker, thereby overwhelming the price impact. Alternatively (or in addition), it may be that red wine drinkers find greater enjoyment trying a variety of wines (Lancaster, 1990), and thus take an opportunity to sample other wines in a restaurant setting. It may also be that price-sensitive wine drinkers self-select away from the reds, most of which are more expensive in higher quality wines.

Finally, the relationship between the *Glass* and *Price* variables may be influencing the apparent insensitivity of red wine demand to price. Whereas white wines available by the glass ranged from \$14 to \$19 on a per bottle basis, red wines by the glass were either \$19 or \$20 per bottle. In addition, there were nine non-glass white wines available from \$13 to \$24, but only three non-glass red wines were below \$25, and of these, none were below \$21. Thus, the parameter for red wines by the glass seems unlikely to reflect only its glass effect; it must also absorb the price impact at the low end of price variability. If the *Glass* variable is dropped for red wines, a negative price effect on demand is observed. This alternative result supports the notion that some customers seek a lower price by selecting wines available by the glass. Nevertheless, the lack of price sensitivity in choosing red wines by the bottle is interesting. Kiefer, Kelly, and Burdett (1994) undertook an experiment in restaurant menu pricing and concluded that substitution between restaurant menu items is quite inelastic. In their experiment, the highest assigned price seemed, if anything, associated with increases in demand.

That this price insensitivity result remains in spite of the inclusion of a low price variable is an unexpected finding, and discounts the notion that a buyer's wish to avoid an impression of choosing the lowest price is creating a false lack of price sensitivity. This inelasticity could be a common situation with regard to restaurant purchases since consumers are generally determining their price level when selecting the restaurant. Further, some buyers with expectations that higher price means higher quality may be offsetting those who are selecting less expensive wines for reasons of economy.

The low price variable could also be considered in the strategic sense for winemakers seeking exposure through restaurant sales. It appears to be a disadvantage for winemakers to be associated with the lowest priced wine in their category, particularly for white wines.

Sensory Characteristic Effects Common to Both Red and White Wines

Posterior samples of the beta-parameters for the five sensory wine characteristics common to both red and white wines are summarized in figure 2, again separated into red and white and ordered by estimated effect.

For red wines, spices were somewhat positive, whereas body and oak were fairly neutral, and the rich descriptor was a negative characteristic. In contrast, for white wines, oak was strongly positive, with rich somewhat positive, spices neutral, and body somewhat negative. Finish was found to be neutral for both reds and whites. Full interpretation of these results is complicated by whether consumers fully understand the descriptors and their typically strong relation to certain varietals. For example, for white wines, oak is principally associated with Chardonnay developed in wooden barrels, while for reds, Cabernet and Zinfandel are generally considered full bodied compared to Pinot Noir.

Sensory Characteristic Effects Unique to Red and White Wines

Posterior samples of the beta-parameters for the sensory wine characteristics unique to red and white wines are summarized in figure 3, again separated into red and white and ordered by estimated effect.

For those flavor and aroma characteristics unique to reds, berry and cherry were fairly strongly positive, while currant, chocolate, and vanilla were neutral, and tannic was fairly strongly negative. For whites, creamy was strongly positive and dry somewhat positive, while citrus was negative; the remaining white characteristics—buttery, tree fruit, melon, honey, and tropical fruit—were mostly neutral.

The negative red wine tannic result can be contrasted with its generally positive quality evaluation by experts. Higher levels of tannin are associated with storability, and are usually expected to mellow by the time the wine reaches its peak consumption period. Storability generally adds to value (Combris, Lecocq, and Visser, 1997), but tannins are less likely to be viewed favorably for immediate wine consumption. Wine stewards may taste such wines when they are first released and before they are offered; thus a wine list should perhaps be adjusted to account for characteristics more appropriate to the time the wines will be consumed.

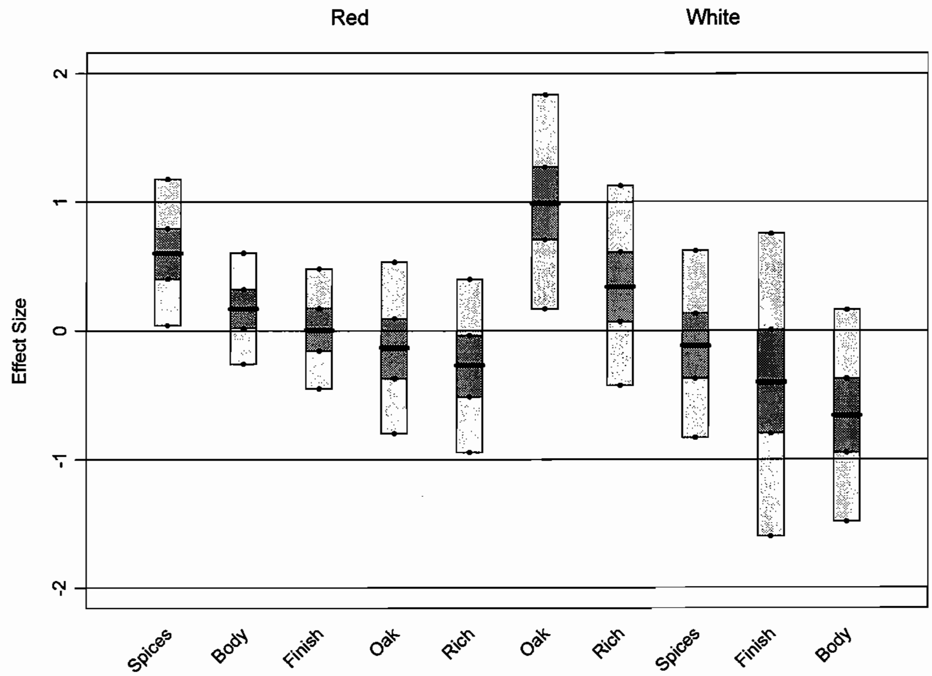

Figure 2. Comparison of effects and precisions for sensory characteristics common to both red and white wines

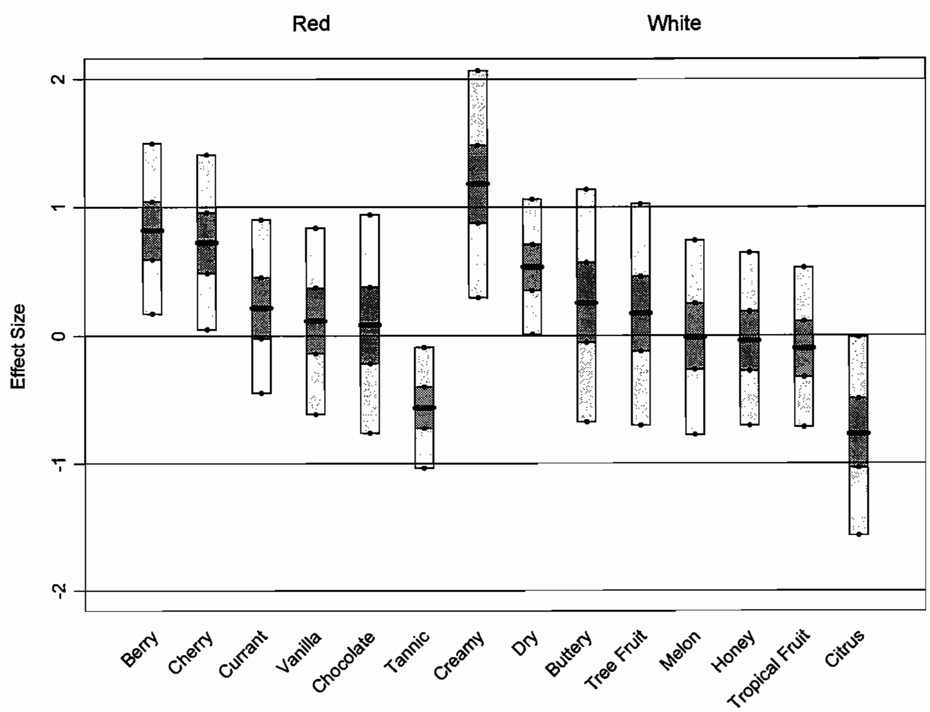

Figure 3. Comparison of effects and precisions for sensory characteristics unique to red and white wines

Value of Characteristics

As outlined in the theoretical model discussion, the results of this type of analysis can be used to derive characteristic values (Nerlove, 1995). In this particular case, only white wine selection was found to be sensitive to price, and thus characteristic impact could only be evaluated for white wines; the estimates of a dollar price equivalent for various factors are reported in the last column of table 6. One way to look at the estimates for the origin-varietal dummy variables is as a price change to accomplish equivalent sales to the base white wine, California Chardonnay. For example, to achieve a demand equivalent to that of California Chardonnay, Oregon Pinot Gris would need to be priced $15 cheaper. Only two of the sensory characteristics—oak and creamy—have an effect larger than $15.

General Findings for Restaurant Wine Analysis

Some of the results found in this analysis may pertain primarily to a limited regional population. For example, the preference for a specific varietal coming from a particular origin may differ by region or country. Still, it is evident from this data set, which is quite different from data used in previous studies, that this origin-varietal information is of interest to customers. Some flavor and sensory characteristics appear to influence wine selection: notably, for white wines, oak, creamy, and dry are positive, and body and citrus are negative; for red wines, spices, berry, and cherry are positive, and tannic is negative. Other characteristics are found to have only minimal impact. Those characteristics which appear to be neutrally considered are perhaps somewhat tempered by their frequent association with certain varietals, so that the origin-varietal information may overwhelm the sensory information.

In some respects, these results are consistent with those reported by Combris, Lecocq, and Visser (1997, 2000), whose price equations for Bordeaux and Burgundy wines found little responsiveness to sensory information. They suggested that the heterogeneity of consumers, and consumers' different preferences for a particular wine, may offset each other in measuring characteristic effects on choice or price. A broader set of wines and longer time period could provide a better statistical basis for examining sensory descriptions. Research in this area could be complemented with survey information or with focus groups.

A number of differences are observed between white and red wine drinkers. In particular, white wine drinkers are price sensitive. Both red and white wine buyers in this population favored well-known origin-varietal combinations over lesser-known combinations and imported wines. The latter result may be peculiar to this particular subset of buyers, a response to the layout of the wines within the wine menu listing, an expectation about imported wine prices, or lack of familiarity with wines from the other varietals and regions.

Conclusions

The approach presented in this analysis to examine wine selection is particularly apt for use in situations where products have a large number of characteristics, and where analysis can be improved by pooling time-series with cross-product information. In particular, the approach is pertinent to examination of consumer preferences between close substitutes where choices are too numerous to examine by experimental methods, where prices are exogenous, and where potential for characteristic impact is relevant for the market.

The principal features of the approach are: (*a*) retail panel data with each cross-section an individual product, (*b*) time periods short enough for product characteristics such as price or replacement products to register, (*c*) a quantity-dependent hedonic model, and (*d*) if needed, a model for estimation which explicitly accounts for large numbers of zero observations.

Using restaurant data for this type of analysis has certain advantages because it provides limits on the factors which could affect demand, while remaining a natural consumer setting. One potential shortcoming is that the dependent variable may contain many zeros. However, the zero-inflated Poisson model is shown to provide a useful means of analyzing this type of data. Restaurants have been used in a limited number of economic experiments, but much potential remains to be realized. Similarly, use of quantity-dependent hedonic models for retail store information could be more widely considered.

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