QUALITY DIFFERENTIATION IN WINE MARKETS

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QUALITY DIFFERENTIATION IN WINE MARKETS

Abstract

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This dissertation consists of three studies that investigate how quality and reputation factors affect the wine market. The models elicit consumer preferences and describe how intrinsic product characteristics, objective properties, and location interactions among wineries affect market prices.

The first study evaluates how sensory properties of Washington State red wines affect consumers' willingness to pay using data from individual level tasting and laboratory measurements. A consumer-preference model serves as a benchmark and three intensity models (consumer-intensity, trained-panel and instrumental measurement) are estimated and compared to quantify sensory effects. The results suggest that astringency has a mostly positive effect, while bitterness has a negative effect. Comparing the accuracy of the three models, the consumer-preference model is the most accurate in predicting consumers' willingness to pay and the instrumental-measurement model is the next best, followed by trained-panel model, and the consumer-intensity model.

The second study investigates how organic classifications affect wine prices and whether organic classification interacts with other product characteristics. The organic classification includes wine is made from organic grapes and “organic handling wine” that is produced via organic methods, which prohibit the usage of artificially derived preservatives, such as sulfites. The hedonic price model is applied to analyze the wine data. The results suggest that organic grape wines command a premium, and organic handling wines sell at discount. Further, the results indicate that estate grown wines obtain an additional premium when selling organic grape wines.

In the third study, the spatial relationships between wineries and wine market values are analyzed. The research question is that whether good neighbors of a winery have positive effects on its own product price. Winery-level data with geographic information system (GIS) coordinates are utilized to understand the spatial relationships among neighboring wineries. Spatial effects for the California and Washington wine industries are examined by performing clustering tests based on wine prices and tasting scores. A spatial lag model is then estimated to test the hypothesis that there are positive effects from neighbors when analyzing the hedonic price equations. The regression results indicate that there exists strong and positive neighbor effect.

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CHAPTER ONE

INTRODUCTION

Wine from United States is referred to as “new world” wine; although the country has a history of over 300 hundred years of producing wine. As of 2010, the United States is the fourth largest wine producing country in the world after the “old world” wine producing countries of France, Italy, and Spain. Within the United States, California is the leading state of wine producing, followed by Washington State, Oregon, and New York. The U.S. wine industry has experience rapid growth and has become a promising market in which to invest. In order to increase the competitiveness of wine, quality differentiation plays an important role in the global market. This dissertation focuses on the following questions concerning quality and reputation: (1) What characteristics affect the market’s perceptions of quality? And (2) how do these quality factors affect wine markets? By understanding the answers to these questions, the industry and researchers can better understand the economics of wine.

Generally, factors affecting wine price and consumer’s preference can be divided into two categories: wine’s sensory properties and wine’s objective characteristics. Wine’s sensory properties refer to wine’s intrinsic attributes, such as astringency, flavor, aroma and bitterness. They describe the real taste of wine and are usually come from blind tasting to insure correct measurement. Even though these sensory properties can serve as good predictive factors, the measurements are subjective and mostly from experiments, which are less practical then using market level resource. Therefore, research on wine price also needs to concern wine’s objective characteristics.

The objective characteristics of wine include extrinsic attributes, such as price, expert ratings, grape variety, vintage, age of wine, region of products and whether they are certain kind of product (such as estate grown wine and organic wine). Consumers can know this information even without tasting wine, since this information is usually included on the label on the bottle. All these factors have potential effects on wine price. Which characteristics affect price significantly and in what way, are particularly interesting problems to be analyzed. Since wine is an experience good which quality cannot be fully accessed before consumption, reputation plays an important role because it serves as a quality signal and a way to assess wine quality prior to consumption. There are two kinds of reputations that are associated with wine. They are the winery's individual (or firm) reputation and the collective reputation shared with other producers from the same production region or appellation. The evolution of reputation may be different for a new wine region, which might not have an established reputation (e.g. Colorado) and an established wine region (e.g. California).

The objective of this dissertation is to analyze how different factors affect the market's assessment of quality and reputation. The three topics which are examined are particularly relevant to wine quality: First, sensory properties which can affect consumer's willingness to pay for Washington State red wine are studied. Second, the impact of organic certifications on the market for wine is analyzed. Third, the effect of spatial interactions among wineries on their product prices is analyzed. These studies will provide valuable information in determining wine quality and offer wine producers suggestions in their decision making.

Sensory Properties and Willingness to Pay

Willingness to pay is the maximum amount of money that an individual would hypothetically bid for a product or service. An established approach to investigate which aspects have significant effects on willingness to pay for food products is to focus on objective characteristics (such as price, brand, and appearance), consumer demographics (such as age, income, and education level), and frequency of consumption. Sensory properties such as taste, aroma, texture, and flavor are typically not included. However, sensory qualities are often the major factors that affect consumers' perception of a product, therefore, it is necessary to include them in accessing consumer's preference. As Brennan and Kuri (2002) indicate that, once consumers develop a preference for a product based on sensory characteristics, it is unlikely for them to change. In this dissertation, relationship between consumer's willingness to pay and different sensory properties are fully analyzed by using data from consumer survey, educated wine panelists and lab measurements.

There are previous studies about how sensory attributes affect market prices for wine. Combris, Lecoq, and Visser (1997) find that when regressing objective characteristics and sensory characteristics on Bordeaux wine prices, the objective cues (such as expert rating score and vintage) are significant, while sensory variables such as tannins content and other measurable chemicals are not. However, more recently, Cardebat and Fiquet (2004) find that sensory characteristics have greater explanatory power compared to previous wine studies. Increasing competition and reductions in information asymmetries in the wine market are two important factors that may explain these more recent results. There are also literatures focusing on interactions between objective characteristics and sensory characteristics.

Veale and Quester (2008) investigate the respective influences of country of origin and price when intrinsic cues are experienced through wine taste tests. They find that the extrinsic cue effects on product evaluation are robust to changes in sensory attributes.

The Market for Organic Wines

As people's awareness of eating healthy and concerns about food quality growing, organic food has become a timely topic and a lot of research has been done in this area. However, "organic" is still a new idea to wine industry; not many studies have focused on it. Therefore, before analyzing how the organic classification affects wine markets, we need to know there are two different organic classifications. The first category is "organic grape wine," which is made from organic grapes that have been grown without the use of chemical fertilizers, pesticides, fungicides and herbicides. The second category is "organic handling wine" that is produced via organic methods, which prohibit the usage of artificially derived preservatives, such as sulfites.

These two kinds of organic classifications may result in wine price differently. For organic grape wine, the raw materials, organically grown grapes, are "green" and generally have higher quality than conventional grapes. Also, it contains a small amount but important preservative, sulfites, which assure the stability of the product and give the wine aging potential. As a result, organic grape wine can command a price premium. On the other hand, organic handling wine is produced sulfites free; this causes a shorter life of the final product, and may result in discount in price. Therefore, people may consider organic grape wine as premium product while treat organic handling wine as inferior good because of its instability and lack of aging potential.

Studies about organic food are abundant in literature. Maguire et al. (2004) estimate the price premium associated with organic baby food using data collected from two U.S. cities and find that the organic price premium is generally equal to 30 to 40 per ounce. Stevens-Garmon et al. (2007) find that organic price premium in fresh produce market increased by 42% between 2001 and 2004 using A.C. Nielsen Homescan data. Also, according to shipment records of an organic marketing cooperative from 2003 to 2005, organic corn and soybean premiums exceeded 100% of the conventional prices, while organic premiums for wheat varieties averaged 85% (Heiman et al., 2008).

However, to my knowledge, no previous studies have analyzed organic factors in the wine industry. This gap in the literature may exist because the organic concept is still in its beginning stages for wine production. The closest work is Delmas and Grant (2008), who examine eco-labeling and eco-certification of organic and biodynamic in the context of wine industry and find that eco-certification has a positive effect on wine prices, while eco-labeling has a negative effect. Delmas et al (2008) provide some background regarding organic and biodynamic practices in U.S. wine industry.

Spatial Analysis of Wineries

If we located every winery in Washington State and California on a map, we can find that wineries are intensively locate in some sub-regions, but none in other areas. This situation can be partially explained by similar grape growing condition or geographic features (*terroir*) defined by American Viticultural Area. However, the reason of why wineries choose to squeeze together instead of evenly share the nature resources still remains question. The idea behind the "First Law of Geography," is that everything is related to everything else, but close things are more related than distance things (Tobler 1970). Perhaps there are benefits to a location that close to a high reputation winery, and these advantages may result from the spillover effect of reputation and management among neighbors.

Previous studies about how region affects wine price are plentiful. Most of these studies include region of production into a hedonic price model and estimate whether this factor has significant effect on wine price. Such as in Noev (2005), Steiner (2004), Angulo et al (2000), Schamel and Anderson (2003) and Costanigro et al (2007), they all find that some regions affect wine price significantly. However, geographic clustering and neighborhood effects (micro level interaction among wineries) in wine industry have not been fully analyzed.

The interaction among close wineries can be important for wine markets. If it positively affects wine price, then new wine producers will want to locate in a high wine price neighborhood to enable themselves to claim a price premium (if there is no consideration of cost). This will result in the formation of collective reputation of a sub-region and also affect the area's dynamic quality equilibrium.

Dissertation Format and Content

This dissertation is presented as three related but stand-alone studies. The first study (Chapter Two) analyzes how sensory qualities of wine, such as astringency, bitterness, aroma, and flavor, affect consumers' willingness to pay, using data sets from consumer survey, trained panel evaluation and laboratory measurements. A double-bounded contingent valuation method is applied to extract consumer's preference over tasting wine. Four models, consumer-preference model, consumer-intensity model, trained-panel model, and instrumental measurement model are estimated and compared. This study is important to Washington State wine producers in that it helps them to understand the effects of sensory properties of wine in consumers' purchase decisions and response to prices, and from there, improve their competitiveness.

The second study (Chapter Three) contributes to the literature of organic product in wine industry. This is the first study to fully analyze the effects of two organic categories, organic grape and organic handling, on wine price. The interactions between organic factors and wine's any characteristics are also carefully investigated. The hedonic price model is applied.

The third study (Chapter Four) accesses the spatial effects for California and Washington wine industries. Winery-level data with geographic information system (GIS) coordinates are utilized to examine the spatial relationships among neighboring wineries. Clustering tests are performed based on wine prices and tasting scores. A spatial lag model is then estimated to test the hypothesis that there are positive effects from neighbors when analyzing the hedonic price equations. This study addresses the importance of spatial interaction processes, externalities and spillover among California and Washington State wine industry.

Chapter 5 is a conclusion part which ties all three studies together.

Summary of Findings

Chapter Two shows that the closer a wine is to a consumer's ideal, the more they are willing to pay. Astringency has a mostly positive effect, and bitterness has a negative effect. Comparing the accuracy of all models, consumer-preference model has the highest predictive power; the instrumental-measurement model is the next best, followed by trained-panel model, and the consumer-intensity model. Therefore, instrumental measurements can be used as an effective alternative to trained panels.

The results from Chapter Three indicate that organic grape can generate premium in wine price, while organic method induces price discount. These findings are consistent with people's general perceptions about organic wine products. Further, the results indicate that estate grown wines obtain an additional premium when selling organic grape wines.

In Chapter Four, clustering tests and spatial econometrics methods are utilized to study California and Washington State wine industries. From clustering tests on wine price and scores, it shows that there is significant clustering pattern. Also, the regression results indicate that there exists strong and positive neighborhood effect: if neighbors of a winery had price premium, it is very likely that the winery also has price advantage. Also, the spatial effect on wine price is stronger and more spreading in California than Washington State.

References

Angulo, A.M., J.M. Gil, A. Gracia and M. Sanchez. (2000). Hedonic Prices for Spanish Red Quality Wine," British Food Journal, 102(7):481-493.

Brennan, C.S., and Kuri, V. (2002). Relationship between sensory attributes, hidden attributes and price in influencing consumer perception of organic foods. Powell et al. (eds.), UK Organic Research 2002: Proceedings of the COR Conference, Aberystwyth, pp. 65-68.

Cardebat, J.-M. and J.-M. Fiquet. (2004). What explains Bordeaux wine prices? Applied Economic Letters 11: 293–96.

Combris, P., S. Lecoq and M. Visser. (1997). Estimation of a hedonic price equation for Bordeaux wine: Does quality matter? The Economic Journal 107: 309–402.

Costanigro, M., Mittelhammer, R.C. and McCluskey, J.J. (2009), Estimating Class-specific Parametric Models under Class Uncertainty: Local Polynomial Regression Clustering in a Hedonic Analysis of Wine Market. *Journal of Applied Econometrics, Early View*

Delmas, M. and Grant, L. (2008) "Eco-labeling Strategies: The Eco-premium Puzzle in the Wine

Industry", AAWE working paper NO.13

Delmas, M., Doctori-Blass, V. and Shuster, K. (2008) "Ceago Vinegarden: How green is your wine? Environmental differentiation strategy through Eco-labels", AAWE working paper NO.14

Goldstein, R., J. Almenberg, A. Dreber, J.W. Emerson, A. Herschkowitsch, and J. Katz. 2008. "Do More Expensive Wines Taste Better?" *Journal of Wine Economics* 3(1): 1-9.

Heiman, R. and Peterson, H. (2008) "Determinants of Premiums Received by Organic Field Crop Producers", *Review of Agricultural Economics*, Volume 30, Number 4, Winter 2008 , pp. 729-749(21)

Jaffe, A.B, Trajtenberg, M. and Henderson, R. (1993), Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *The Quarterly Journal of Economics, vol. 108, No.3., 577 – 598*

Kaye-Blake, W., O'Connell, A. and Lamb, C. (2007), Potential Market Segments for Genetically Modified Food: Results from Cluster Analysis, *Agribusiness, Vol. 23 (4), 567 – 582*

Maguire, KB. , Owens, N., and Simon, NB. (2004). "The Price Premium for Organic Babyfood: A

Hedonic Analysis" *Journal of Agricultural and Resource Economics,* 29(1): 132-149

Noev, N., (2005), Wine Quality and Regional Reputation: Hedonic Analysis of the Bulgarian Wine Market, *Eastern European Economics*, *Volume 43, Number 6 / November-December 2005, 5 – 30*

Porter, M. (2000), Location, Competition, and Economic Development: Local Clusters in a Global Economy. *Economic Development Quarterly, Vol.14 No.1,* 15-34.

Schamel, G. and K. Anderson. (2003). "Wine Quality and Varietal, Regional and Winery Reputations: Hedonic prices for Australia and New Zealand," Economic Record 79:246.

Steiner, B., (2004), French Wines on the Decline? Econometric Evidence from Britain, *Journal of Agricultural Economics, Volume 55, Number 2, July 2004 , pp. 267-288(22)*

Stevens-Garmon, J., Huang, C. L., Lin, B. H., (2007). Organic demand: a profile of consumers in the fresh produce market. *Choices* 22, 109–115.

Tobler, W. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography* 46: 234–40.

Veale, Roberta and Pascale Quester (2008). "Consumer Sensory Evaluations of Wine Quality: The Respective Influence of Price and Country of Origin." Journal of Wine Economics 3(1): 10-29.

CHAPTER TWO

WILLINGNESS TO PAY FOR SENSORY PROPERTIES IN WASHINGTON STATE RED WINES

Chapter Abstract: In this article, we evaluate how sensory qualities of wine, such as astringency, bitterness, aroma, and flavor, affect consumers' willingness to pay for wine. In order to accomplish this objective, we utilize data collected from untrained consumers, a trained panel, and laboratory measurements of tannin intensity. From this data, a consumer-preference model, consumer-intensity model, a trained-panel model, and an instrumental measurement model are estimated and compared. Overall, the consumer-preference model is the most accurate in predicting consumers' willingness to pay. As expected, the closer a wine is to a consumer's ideal, the more they are willing to pay. Astringency has a mostly positive effect, and bitterness has a negative effect. Comparing the accuracy of the other models, the instrumental-measurement model is the next best, followed by trained-panel model, and the consumer-intensity model. This suggests that the instrumental measurements can be used as an effective alternative to trained panels. This is important because trained panels are less practical to use on an ongoing basis.

Key words: Willingness to Pay (WTP), sensory quality

Introduction

In assessing consumers' preferences for food products, an established approach is to investigate which aspects have significant effects on willingness to pay from among objective characteristics (such as price, brand, and appearance), consumer demographics (such as age, income, and education level), and frequency of consumption. Intrinsic factors such as taste, aroma, texture, and flavor are typically not included in the willingness-to-pay analysis. This is unfortunate since sensory qualities are often the major factors that affect consumers' perception of a product, which, in turn, affect their purchase behavior. Brennan and Kuri (2002) find that once consumers develop a preference for a product based on sensory characteristics, it is unlikely for them to change. Thus, sensory characteristics have a major influence on repeat purchases.

The case of wine is a bit more complicated. As Goldstein et al (2008) discuss, when symbolic content is an important part of consumption, the enjoyment of a product might become decoupled from its innate qualities. Novice or occasional wine drinkers may rely on experts (e.g. rating scores) to inform themselves about what is desirable. There is a literature that uses sensory attributes to examine consumer preferences, which may differ across the novice wine consumer and the connoisseur. There are several hedonic price (Rosen, 1978) studies that examine how sensory attributes affect market prices for wine. Combris, Lecoq, and Visser (1997) find that when regressing objective characteristics and sensory characteristics on Bordeaux wine prices, the objective cues (such as expert rating score and vintage) are significant, while sensory variables such as tannins content and other measurable chemicals are not. Possible explanations for the insignificance of sensory cues in wine are the difficulty of isolating the effect of each chemical and that only a small percentage of wine purchasers are connoisseurs who have developed a palette that can consistency identify differences across wines. In a more recent study, Cardebat and Fiquet (2004) find that sensory characteristics have greater explanatory power compared to previous wine studies. Increasing competition and reductions in information asymmetries in the wine market are two important factors that may explain these more recent results.

Interactions between objective characteristics and sensory characteristics have also been studied in the response to wine tastings. Goldstein et al (2008) find that in blind taste tests, the correlation between price and enjoyment was small and negative for their non-expert wine consumer. In contrast, for individuals with wine training, there is a non-negative relationship between price and enjoyment. Veale and Quester (2008) investigate the respective influences of country of origin and price when intrinsic cues are experienced through wine taste tests. They find that the extrinsic cue effects on product evaluation are robust to changes in sensory attributes.

In this article, we evaluate how intrinsic cues or sensory qualities of wine, such as astringency, bitterness, aroma, and flavor, affect consumers' willingness to pay for wine, utilizing three different but related measurement approaches. In order to accomplish this objective, we utilize data collected from untrained consumers, a trained panel, and laboratory measurements of tannin intensity (representative of astringency intensity). From this data, a consumer-preference model, consumer-intensity model, a trained-panel model, and an instrumental measurement model are estimated and compared.

The results from this study can useful to the wine industry in their understanding of how sensory properties of wine affect consumers' purchase decisions and response to prices. The consumer-preference model in this article serves as a benchmark because it contains consumer's subjective preferences for the sensory attributes. The consumer-intensity model is estimated to evaluate its effectiveness relative to the consumer-preference model. The sensory-intensity evaluations applied in this study are consumer's subjective feelings about these attributes. The trained-panel model and instrumental measurement model predict with objectively measured variables what consumers prefer based on their subjectively held perceptions, especially for astringency intensity. The results can be evaluated for accuracy against the consumer preference model to understand the usefulness of these measurements in predicting consumer responses.

Data

The data used in this analysis contains three parts: a consumer panel, a trained panel, and an instrumental measurement of wine's astringency level.

<u>Consumer Panel</u>

The consumer data was collected through a consumer tasting survey using Washington State red wines conducted at the Sensory Facilities at Washington State University in 2007. The panelists were recruited from the area with the criterion that they consume red wine at least twice a month. All participants signed an informed consent form and the project was approved for human subject participation by an Institutional Review Board. Participants were awarded a small non-monetary incentive for participation.

The consumers were asked to complete a demographic questionnaire and answer questions regarding their wine consumption and wine experiences. The consumer panel consisted of 60 volunteer participants, 27 female and 33 male, all between the ages of 21 and 79, with mean 39.5 and median 37.5. Although men are slightly over-represented in the sample, the other demographic variables fall within the population values at the state level. Table 1 presents summary statistics and comparison of consumer's socio-demographic variables.

Three young 2006 Cabernet Sauvignon wines (different in their tannin contents) were presented to the consumer participants for evaluation. Prior to the sensory panel evaluation, wines were maintained at room temperature for at least 24 hours. The visual extrinsic cues were suppressed or homogenous (e.g. only red wines are included and presented in a wine glass). The wines were presented in a random serving order, one wine sample at a time, for a total of three wine samples. Each wine was coded with a three-digit code, and red lights were used during the evaluations to mask any color differences between wines. Each sample consisted of 30 milliliters wine, poured into a tasting glass, and covered with a plastic petri dish. Consumers were instructed to rinse with water and eat crackers to cleanse their palates between samples.

The consumers evaluated each of the three wines to assess the overall desirability and the attributes of aroma, flavor, astringency and bitterness. For desirability evaluations, a 9-point Liking scale was used, anchored with 1 as "dislike extremely," 5 as "neither like nor dislike," and

9 as “like extremely.” These types of scales are referred to as “hedonic ratings.” Hedonic ratings were collected for overall acceptance, aroma, flavor, astringency and bitterness. Consumers were also asked to rate the intensity of aroma, flavor, astringency and bitterness along a 9-point scale with 1 equal to an extremely low intensity, and 9 equal to an extremely high intensity. In order to assess the willingness to pay, contingent valuation questions were asked in conjunction with the taste tests. Overall, there are 180 observations on sensory preferences and intensity evaluations from consumer panel. Table 2 presents summary statistics for the variables representing the sensory characteristics of consumers.

Trained Panel

Eleven volunteers were recruited and were selected to participate in the trained panel. The panel consisted of two males and nine females between the ages of 22 and 54. For their participation, panelists received a small non-monetary compensation following each training or evaluation session. Prior to formal evaluation sessions, panelists were trained over five sessions. Panelists were taught to identify and rate astringency through the presentation and discussion of Cabernet Sauvignon wines of varying tannin levels: 119 milligrams/liter catechin equivalents (CE) to 1150 milligrams/liter CE tannin.[1] Astringency standards of three levels were used: low (0.6 grams tannic acid and 0.25 grams alum), medium (1.2 grams tannic acid and 0.5 grams alum), and

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[1] These were determined using the assay described by Harbertson et al. (2003) and through the evaluation of astringency standards.

high (2.4 grams tannic acid and 1.0 grams alum). All standards were prepared in a base red table wine. Panelists were also trained to recognize bitterness using standards of 0.5 grams/liter quinine sulfate, 0.1 grams/liter quinine sulfate, and 0.2 grams/liter quinine sulfate for low, medium and high, respectively, prepared in base red table wine.

Following initial training with standards, panelists were trained using red wines of different anthocyanin, tannin, SPP and LPP concentrations as determined using the protein precipitation assay described by Harbertson et al. (2003). Trained panelists evaluated both bitterness and astringency using a 15-centimeter unstructured line scale. Panelists were trained so that low perceived astringency or bitterness ranged from zero to five centimeters on a 15 centimeter unstructured line scale, medium from 5.1 to 10 centimeters, and high from 10.1 to 15 centimeters. Wine samples were evaluated by the panelists, rated, and discussed to ensure a consensus was reached as to the level of astringency or bitterness for that particular wine sample. The trained panelists were assessed for their reliability and validity prior to the start of the formal evaluations.

For the formal evaluations, the trained panel evaluated the same three wine samples as the consumer participants evaluated. Three young 2006 Cabernet Sauvignon wines (low, medium and high astringency) were presented to the trained panel, in replicate, in a random serving order and coded with three-digit codes. Trained panelists were instructed to rinse with water and eat crackers to cleanse their palates between samples. The panelists evaluated each wine in replicate (for a total of 4 evaluations) for both astringency and bitterness along a 15-centimeter unstructured line scale. Summary statistics for evaluations of the sensory characteristics from trained panel are presented in Table 3.

Instrumental Measurements

Astringency plays an important role in taste differences across wines. In this research, we are particularly interested in the effects of astringency on consumer's willingness to pay. Therefore, we include an instrumental measurement of the wine's astringency level in our regression analyses. The three young 2006 Cabernet Sauvignon wines evaluated by consumers and trained panelists were measured and distinct by their astringency levels, since tannin content is a direct way to represent astringency intensity. Three different levels of tannin are applied: 997 milligrams/liter CE, 673 milligrams/liter CE, and 213 milligrams/liter CE as determined by the modified protein precipitation assay (Harbertson et al., 2003). Table 4 presents a summary of the instrumental measurements of the wine's astringency.

Methodology

Willingness-to-pay analysis differs from hedonic price studies that predict an equilibrium market price. In a willingness-to-pay analysis of sensory characteristics, the objective is to examine the maximum an individual consumer would pay for the product in question and how the sensory properties of the wine influence this amount.

The contingent valuation (CV) method is a technique that is commonly used to estimate willingness to pay.[2] In pursuit of this objective, a double-bounded model question sequence (Hanemann, Loomis, and Kanninen 1991) was included in the survey.[3] In the double-bounded model, each participant is presented with two bids. The level of the second bid is contingent upon the response to the first bid. If the individual responds "yes," meaning that he or she is willing-to-pay the amount of the first bid (B_0), then the individual is presented with a second higher bid (B_H). On the other hand, if the individual responds "no," meaning that he or she is not willing to pay the amount of the first bid, then he/she is presented with a second discounted bid (B_L). The four possible responses to the bid scenarios are: (1) "no" to both bids, (2) a "no" followed by a "yes", (3) a "yes" followed by a "no" and, (4) "yes" to both bids.

The respondent's true willingness to pay for wines will lie in the range isolated by the response to these questions. The second bid, B_L or B_H, in conjunction with the response to the initial preference decision, allows a lower bound and an upper bound to be placed on the respondent's unobservable true willingness to pay. Let WTP_i denote an individual's willingness to pay (bid function) for the tasted wine. The following discrete outcomes (D_g) of the bidding process are

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[2]For further information, including recent reviews and comparison across models estimable from CV data with reiteration see, for example, Flachaire and Hollard (2006).

[3]There is a literature on the appropriate number of iterations to include in the bidding procedures used in the CV method. Cameron and Quiggin (1994) evidenced the problem of anchoring/starting point bias with iterations of bids. There is some bias with the double-bounded model, primarily due to inconsistencies which may be present between the consumers' first and subsequent bids (Hanemann and Kanninen, 1999).

Group

$$D_g = \begin{cases} 1 & WTP_i < B_D \\ 2 & B_L \le WTP_i < B_0 \\ 3 & B_0 \le WTP_i < B_H \\ 4 & B_H \le WTP_i \end{cases} . \qquad (1)$$

Respondents who indicated they require no discount and would pay the premium price B_H fall into the fourth group (D_4). Those who indicated they require no discount and would pay a premium of less than B_H fall into the third group (D_3); respondents who required a discount greater than or equal to B_L fall into the second group (D_2). As a result, the first group (D_1) contains respondents indicating the lowest willingness to pay. Consumers in this group are not willing to purchase the tasted wine at the discount offered.

The sequence of questions isolates the range in which the respondent's true willingness to pay lies, placing it into one of the following four intervals: $(-\infty, B_L)$, $[B_L, B_0)$, $[B_0, B_H)$, or $[B_H, +\infty)$. The second bid, in conjunction with the response to the initial preference decision, allows both an upper and a lower bound to be placed on the respondent's unobservable true willingness to pay. The willingness-to-pay function is represented as:

$$WTP_i = \alpha - \rho B_i + \lambda' z_i + \varepsilon_i \quad \text{for} \quad i = 1, \ldots, n \qquad (2)$$

where z_i represents a vector of explanatory variables such as consumers' demographics and preferences over sensory attributes in “consumer-preference model”, their subject intensity evaluations in “consumer-intensity model”, educated sensory evaluation in “trained-panel model” and objective measurement of astringency in “instrumental measurement model”. The final bid that a respondent reaches is represented by B_i. The variable ε_i is an error term, which captures unmeasured characteristics and is assumed to follow a cumulative distribution G with mean 0 and variance σ^2, i.e. $\varepsilon \sim G(0,\sigma^2)$. The parameters ρ and λ' are unknowns and need to be estimated, as well as the intercept α .

We will apply maximum likelihood to estimate these parameters and optimization program is performed in GAUSS. Under the distribution assumptions, the probabilities for the above choice groups can be obtained as:

$$prob(D=j)=\begin{Bmatrix} G(\alpha-\rho B_D+\lambda' z) \\ G(\alpha-\rho B_0+\lambda' z)-G(\alpha-\rho B_D+\lambda' z) \\ G(\alpha-\rho B_p+\lambda' z)-G(\alpha-\rho B_0+\lambda' z) \\ 1-G(\alpha-\rho B_p+\lambda' z) \end{Bmatrix} \text{ for } \text{j}=\begin{Bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{Bmatrix} \tag{3}$$

Therefore, the log likelihood function is constructed as

$$L=\sum_i \begin{Bmatrix} I_{D_i=1}\ln G(\alpha-\rho B_{D_i}+\lambda' z_i) \\ +I_{D_i=2}\ln[G(\alpha-\rho B_{0_i}+\lambda' z_i)-G(\alpha-\rho B_{D_i}+\lambda' z_i)] \\ +I_{D_i=3}\ln[G(\alpha-\rho B_{p_i}+\lambda' z_i)-G(\alpha-\rho B_{0_i}+\lambda' z_i) \\ +I_{D_i=4}\ln[1-G(\alpha-\rho B_{p_i}+\lambda' z_i)] \end{Bmatrix} \tag{4}$$

where $I_{D_i=j}$ is an indicator function for the occurrence of $D_i = j$, where $j \in J \equiv \{1,2,3,4\}$, and subscript *i* denotes the *i*th individual observation. In the empirical implementation of the model, G(.) is defined to be the standard logistic distribution.

The marginal effects of explanatory variables in these models are essentially the difference between when the parameter estimate is added to the intercept and when it is not:

$$\text{Marginal Effect of } \tilde{\lambda}_k = \frac{\tilde{\alpha} + \tilde{\lambda}_k}{\tilde{\rho}} - \frac{\tilde{\alpha}}{\tilde{\rho}} = \frac{\tilde{\lambda}_k}{\tilde{\rho}} \qquad (5)$$

Marginal effects are estimated for all models.

Estimation Results

Four models are estimated based on equation (2). The estimation results are presented in Tables 5 - 8. The corresponding estimated marginal effects and their probability values are are presented in Tables 9 – 12. The consumer-preference model contains subjective consumer evaluation variables and demographic variables. Variables include *aroma, flavor, astringency* and *bitterness*, together with *gender, age* and *frequency*. The variables *aroma, flavor, astringency* and *bitterness* indicate preferences for each attribute, respectively. *Gender* is an indicator variable that represents being female. *Age* represents the participant’s age in years. *Frequency* is an indicator variable coded as one if the respondent stated that he or she purchases wine at least once a week and zero otherwise.

The consumer-preference model reflects those sensory attributes that consumers consider when making wine purchases. As expected, the bid (or price) has a negative relationship, indicating consumers are less likely to buy the product as the price increases. The signs of the coefficients for *aroma, flavor*, *astringency* and *bitterness* are positive as expected, indicating that the closer the wines is the consumer's ideal, the more he or she would be willing to pay for it. However, the estimate for *bitterness* is not statistically significant at the level of 0.1, which suggests that this sensory attribute is less important to untrained consumers. In terms of demographic variables, *gender* does not play significant role in explaining the willingness to pay for wine. *Age* affects willingness to pay significantly; the results suggest that young people are more likely to be willing to pay a premium. *Frequency* does not play a significant role in explaining the willingness to pay in the consumer model.

The consumer-intensity model includes sensory evaluations in terms of intensity of the attribute from the untrained consumer's points of view. The variables in this model include *bid, aroma intensity, flavor intensity, astringency intensity, astringency intensity squared,* and *bitterness intensity,* along with *gender, age* and *frequency*. The new variables represent the consumer's assessments of the intensities of aroma, flavor, astringency and bitterness, respectively. A quadratic term of astringency intensity evaluation is added to the model to allow for the relationship between astringency intensity and consumer's willingness to pay to be non-linear. If consumer willingness to pay is quadratic in astringency intensity, then there would be an ideal point of astringency from the consumer's point of view.

In terms of results in the consumer-intensity model, *bid, flavor intensity, bitterness* *intensity, astringency intensity squared* and *age* have statistically significant effects on their willingness to pay, but *astringency intensity* and *aroma intensity* are not. The sign on *flavor intensity* is positive, indicating consumers prefer wines with more intense flavors. *Bitterness intensity* has negative effect on consumer's willingness to pay; indicating consumers are less likely to buy bitter wines. The *astringency intensity* is curious. Only the squared term is statistically significant. The negative effect of the *astringency intensity squared* variable suggests that high levels of astringency negatively affect willingness to pay.

The trained-panel model utilizes professional measurements for astringency and bitterness intensities. It includes variables *bid*, *trained-panel astringency, trained-panel astringency squared* and *trained-panel bitterness.* We differentiate *trained-panel astringency, trained-panel astringency squared* and *trained-panel bitterness* from the intensity variables that are utilized in consumer-intensity model. These are trained-panel measurements, evaluations from an educated group, which correspond more closely to instrumental measurements than to the consumer evaluations. By using trained-panel evaluations as explanatory variables in a model of untrained consumers' willingness to pay, one can gain a better understanding about how the sensory intensity of the tasting wine affect common consumer's willingness to pay. The coefficients associated with *trained-panel astringency* and *trained-panel bitterness* are both significant at the 0.05 level with a positive effect from astringency and a negative influence from bitterness. However, *trained-panel astringency squared* is far from significant, which suggests there is no maximum optimal level of astringency within the sample wines that were tasted.

Comparing the trained panel model to consumer-intensity model, we find that the trained panel findings are consistent with the consumer model in the case of bitterness. They are willing to pay less for a bitter wine. However, a comparison of these two models shows an interesting result for astringency. *Trained-panel astringency* has a positive and significant effect in the trained-panel model, while only the squared astringency levels have a significant effect in the consumer model. However, it may simply be the case that novice wine consumers cannot accurately assess astringency intensity correctly.

The instrumental measurement model only considers two independent variables: astringency level (tannin content level) and its square term. There are three tannin content levels (997 mg/L, 673 mg/L and 213 mg/L), and we scale them by 1/100. The coefficient for astringency is positive and highly significant (at the 0.01 level), indicating that higher astringency intensity can cause wine consumers to be willing to pay a higher premium. Also, for astringency squared, it does affect WTP significantly. This corroborates the results of the trained panel model.

Measures of goodness of fit across the models are compared using the fully correctly classified cases (FCCC) method as suggested by Kanninen and Khawaja (1995). This method calculates the percentage of respondents that the models correctly classified into the appropriate group (yes/yes, yes/no, no/yes, and no/no). A higher value of percentage of correct predictions indicates a better model fit. Note that pure chance results in 25% correct predictions, since there are four categories. Overall, as expected, the consumer model is the most accurate predictive model considered in this paper, correctly predicting 67% of consumer responses. The consumer-intensity model using consumer's untrained evaluations for sensory intensity correctly predicted 60% of consumer responses. The trained panel model correctly predicted 61% of responses. Finally, the instrumental measurement model of astringency intensity level correctly predicted 62% percept of responses. Our percentages of correct predictions compares favorably to other studies. For example, Kanninen and Khawaja (1995), in studying willingness to pay for water supply reliability, correctly predicted willingness to pay categories 35% of the time.

Comparing the prediction accuracy of the models, the instrumental-measurement model achieves even a slightly higher level of accuracy in percentage of correct predictions at 62% compared to the trained panel model. This suggests that the instrumental measurements can be used as an effective alternative to trained panels. This is important because trained panels are less practical to use on an ongoing basis. The consumer-preference model contained subjective sensory perceptions that consumers consider when making repeat wine purchases. The hindrance in using such a model is that many of the variables are intrinsic and subjective. Further, since consumers are highly heterogeneous, taste and preferences vary among individuals. The signs for the coefficients on all the sensory variables are positive, indicating that the closer the wine comes to a consumer's ideal, the more they are willing to pay. With the instrumental-measurement and trained-panel models, the purpose was to estimate, with objectively measured variables, what consumers would actually be willing to pay given their subjectively held perceptions.

Conclusions

Four models of willingness to pay for internal quality characteristics in Washington State red wines were estimated via maximum likelihood method: (1) a consumer-preference model,

(2) a consumer-intensity model, (3) a trained panel model, and (4) an instrumental measurement model. The estimation results show that all variables in all four models have the expected signs. The consumer-preference model serves as a benchmark in this paper. The signs for the coefficients on all the sensory variables are positive, though some of the coefficients are not significant. As expected, the closer a wine is to a consumer's ideal, the more they are willing to pay. The shortcoming in the consumer-preference model is that the variables are intrinsic and subjective since it contains subjective sensory perceptions. The consumer-intensity model represents novice wine buyers' preferences about sensory intensity. The results show that untrained consumers are willing to pay more for high flavor intensity and less bitter wines.

With the trained-panel and instrumental-measurement models, the purpose was to estimate consumer willingness to pay for wines with professional and objectively measured variables. Bitterness intensity has a negative and significant influence on willingness to pay in trained-panel model. The impact of astringency in trained-panel and instrumental-measurement models is positive. However, only astringency squared is significant (negative) in the consumer intensity model. It may be the case that consumers view astringency as a signal of quality in wine (but they do not like too much) or they cannot accurately evaluate astringency intensity.

The effectiveness of the instrumental measurements in predicting consumer willingness to pay is promising. This suggests that instrumental measurements can be used as an effective alternative to trained panels. This is important because trained panels are less practical to use on an ongoing basis. These conclusions can assist wine grape growers and winemakers in their assessments of the importance of specific quality properties for increasing the competitiveness of the industry.

References

Brennan, C.S., and Kuri, V. (2002). Relationship between sensory attributes, hidden attributes and price in influencing consumer perception of organic foods. Powell et al. (eds.), UK Organic Research 2002: Proceedings of the COR Conference, Aberystwyth, pp. 65-68.

Cardebat, J.-M. and J.-M. Fiquet. 2004. What explains Bordeaux wine prices? Applied Economic Letters 11: 293–96.

Carew, R. (2000). A hedonic analysis of apple prices and product quality characteristics in British Columbia. Canadian Journal of Agricultural Economics, 48, 241-257.

Cameron, T. and Quiggin, J. (1994). Estimation using contingent valuation data from a ‘dichotomous choice with follow up’ questionnaire. *Journal of Environmental Economics and Management*, 27, 218-234.

Combris, P., S. Lecoq and M. Visser. 1997. Estimation of a hedonic price equation for Bordeaux wine: Does quality matter? The Economic Journal 107: 309–402.

Goldstein, R., J. Almenberg, A. Dreber, J.W. Emerson, A. Herschkowitsch, and J. Katz. 2008. “Do More Expensive Wines Taste Better?” *Journal of Wine Economics* 3(1): 1-9.

Hanemann, W.M. (1989). "Welfare Evaluations in Contingent Valuation Experiments with Discrete Response Data: Reply." *American Journal of Agricultural Economics* 71:1057-1061.

Hanemann, W.M. and Kanninen, B. (1999). The statistical analysis of discrete-response CV data. In Bateman, I.J. and Willis, K.G. (Eds.) Valuing environmental preferences: theory and practice of the contingent valuation method in the US, EU, and developing countries. Oxford, NY: Oxford University Press, pp. 302-442.

Kajikawa, C. (1998). Quality level and price in the Japanese apple market. Agribusiness,14, 227-234.

Kanninen, B.J. and M.S. Khawaja. (1995). Measuring goodness of fit for the double-bounded logit model. American Journal of Agricultural Economics 77(4): 885-890

Lecocq, Sebastien and M. Visser (2006). "What Determines Wine Prices: Objective vs. Sensory Characteristics," *Journal of Wine Economics*, vol.1, No. 1: 42-56.

McCluskey, J.J. Mittelhammer, R. Marin, A. and Wright, K. (2007). Effect of Quality Characteristics on Consumers' Willingness to Pay for Gala Apples. Canadian Journal of Agricultural Economics 55 217–231.

Veale, Roberta and Pascale Quester (2008). "Consumer Sensory Evaluations of Wine Quality: The Respective Influence of Price and Country of Origin." *Journal of Wine Economics* 3(1): 10-29.

Table 2.1 Summary of Consumer Panel Demographic

	Participant	Washington
Respondents	60	
Median age (years)	37.5	36.8
	(std. dev. 14.94)	
Male	55%	49.80%
Female	45%	50.20%
Frequency		
Daily	20%	
At least once a week	30%	
Once every 2 weeks	30%	
Once a Month	10%	
Only on special occasions	10%	

Table 2.2 Summary Statistics for the Consumer Panel

Consumer Panel Ratings of wine (n=180)					
	Description	Mean	Min	Max	Std.
Aroma	Aroma preference	4.79	1	9	2.02
Flavor	Flavor preference	4.67	1	9	2.01
Astringency	Astringency preference	4.87	1	9	1.79
Bitterness	Bitterness preference	4.57	1	9	1.78
AromaIntC	Aroma intensity evaluated by consumers	5.07	1	9	2.08
FlavorIntC	Flavor intensity evaluated by consumers	4.98	1	9	1.92
AstrIntC	Astringency intensity evaluated by consumers	4.87	1	9	2.03
BitIntC	Bitterness intensity evaluated by consumers	4.22	1	9	2.08

Table 2.3 Summary Statistics for the Trained Panel

Trained Panel Ratings of Wine (n = 132)					
	Description	Mean	Min	Max	Std. Error
AstrInt	Astringency intensity evaluated by trained panelists	6.28	0.4	14.1	3.82
BitInt	Bitterness intensity evaluated by trained panelists	5.14	0.2	13.2	3.18

Table 2.4 Summary Statistics for the instrumental measurement of wine's astringency

Tannin Content	Scaled value
Concentration of 997 milligram/LITER catechin equivalents	9.97
Concentration of 673 milligram/LITER catechin equivalents	6.73
Concentration of 213 milligram/LITER catechin equivalents	2.13

Table 2.5 Estimation results for Consumer-preference model

Parameters	Description	Estimates	Std. error	z-statistic	p-value
ρ	Final Bid	-0.4823	0.0564	-8.5470	0.0000
α	Intercept	-0.6078	1.0158	-0.5980	0.5496
λ_1	Aroma	0.1950	0.1177	1.6570	0.0975
λ_2	Flavor	0.5403	0.1403	3.8510	0.0001
λ_3	Astringency	0.3838	0.1357	2.8290	0.0047
λ_4	Bitterness	0.1330	0.1230	1.0810	0.2799
λ_5	Gender	-0.1745	0.3709	-0.4710	0.6380
λ_6	Age	-0.0580	0.0145	-4.0000	0.0001
λ_7	Frequency	-0.1184	0.3654	-0.3240	0.7460

Table 2.6 Estimation results for Consumer-intensity model

Parameters	Description	Estimates	Std. error	z-statistic	p-value
ρ	Final Bid	-0.3708	0.0437	-8.4830	0.0000
α	Intercept	3.7568	1.0059	3.7350	0.0002
λ_1	AromaIntC	0.0225	0.0843	0.2660	0.7899
λ_2	FlavorIntC	0.4005	0.1063	3.7680	0.0002
λ_3	AstrIntC	0.0185	0.0942	0.1960	0.8444
λ_4	AstrIntC2	-0.0806	0.0447	-1.8020	0.0715
λ_5	BitIntC	-0.2599	0.0898	-2.8940	0.0038
λ_6	Gender	-0.1504	0.3296	-0.4560	0.6482
λ_7	Age	-0.0536	0.0133	-4.0360	0.0001
λ_8	Frequency	0.1358	0.3342	0.4060	0.6845

Table 2.7 Estimation results for Trained sensory panel model

Parameters	Description	Estimates	Std. error	z-statistic	p-value
ρ	Final Bid	-0.3219	0.0456	-7.0620	0.0000
α	Intercept	2.8332	0.5855	4.8390	0.0000
λ_1	AstrInt	0.1352	0.0512	2.6420	0.0082
λ_2	AstrInt2	-0.0070	0.0130	-0.5420	0.5876
λ_3	BitInt	-0.1299	0.0602	-2.1570	0.0310

Table 2.8 Estimation results for instrumental measurement model

Parameters	Description	Estimates	Std. error	z-statistic	p-value
ρ	Final Bid	-0.3266	0.0393	-8.3070	0.0000
α	Intercept	2.3591	0.4358	5.4130	0.0000
λ_1	Tannin Content	0.1537	0.0521	2.9490	0.0032
λ_2	Tannin Content2	-0.0266	0.0210	-1.2660	0.2055

Table 2.9 Marginal Effects in the Consumer-preference Model

Parameters	Description	Marginal Effect	Standard error	P-value
λ_1	Aroma	0.4043	0.2517	0.1082
λ_2	Flavor	1.1204	0.3432	0.0011
λ_3	Astringency	0.7958	0.3127	0.0109
λ_4	Bitterness	0.2757	0.2582	0.2857
λ_5	Gender	-0.3619	0.7693	0.6381
λ_6	Age	-0.1202	0.0361	0.0009
λ_7	Frequency	-0.2454	0.7587	0.7463

Table 2.10 Marginal Effects in the Consumer-intensity Model

Parameters	Description	Marginal Effects	Standard Errors	P-values
λ_1	AromaIntC	0.0606	0.2274	0.7900
λ_2	FlavorIntC	1.0799	0.3327	0.0012
λ_3	AstrIntC	0.0499	0.2541	0.8444
λ_4	AstrIntC2	-0.2173	0.1250	0.0820
λ_5	BitIntC	-0.7008	0.2667	0.0086
λ_6	Gender	-0.4054	0.8911	0.6491
λ_7	Age	-0.1445	0.0423	0.0006
λ_8	Frequency	0.3662	0.9036	0.6853

Table 2.11 Marginal Effects in the Trained panel Model

Parameters	Description	Marginal Effects	Standard Errors	P-values
λ_1	AstrInt	0.4200	0.1764	0.0173
λ_2	AstrInt2	-0.0219	0.0404	0.5885
λ_3	BitInt	-0.4036	0.2017	0.0454

Table 2.12 Marginal Effects in the Instrumental measurement Model

Parameters	Description	Marginal Effects	Standard Errors	P-values
λ_1	Tannin Content	0.4706	0.1742	0.0069
λ_2	Tannin Content2	-0.0815	0.0653	0.2118

CHAPTER THREE

DOES “ORGANIC” MAKE A DIFFERENCE IN THE WINE INDUSTRY?

Chapter Abstract: This article investigates how organic classification affects wine prices and whether organic classification interacts with other product characteristics. The organic classification includes two distinct categories of wines. One category is wine is made from organic grapes that have been grown without the use of chemical fertilizers, pesticides, fungicides and herbicides. The second category is "organic handling wine" that is produced via organic methods, which prohibit the usage of artificially derived preservatives, such as sulfites. Since this kind of product is not stable, consumers may treat it as inferior good. The hedonic price model is applied to analyze the wine data. From these analyses, we find that while organic grape wines command a premium, and organic handling wines sell at discount. Further, the results indicate that estate grown wines obtain an additional premium when selling organic grape wines. This is the first study to analyze organic factors for wine industry.

Key words: Organic grape wine, Organic handling wine, Hedonic regression

Introduction

In this article, we undertake the empirical test of the "organic" effect on prices in the wine industry. There are two kinds of "organic" wines. The organic classification includes two distinct categories of wines. One category is wine is made from organic grapes that have been grown without the use of chemical fertilizers, pesticides, fungicides and herbicides. Therefore, the raw materials of it are organically grown grapes. One point should be noticed about organic grape wine: it can include added sulfites, a preservative in wines which has strong antimicrobial properties and some antioxidant properties, even though only in extremely small quantities. Debates over adding sulfites into wine production are ongoing within organic winemaking community because the health effects or consequences of sulfites are unclear and a small percent of the population does suffer a reaction to sulfites. However, regardless the controversial role of sulfites, they still serve as important factors for the quality of wine. Consequently, consumers may treat "organic grape wine" as a high quality product because of its environmentally friendly and stable characteristics. U.S. wineries or vineyards can inform consumers about their organic raw materials by getting an organic crop certificate from the U.S. Department of Agriculture (USDA).

The second category is "organic handling wine," which is produced via organic methods. Organic handling methods prohibit the usage of artificially derived preservatives, such as sulfites. Therefore, organic handling wine is sulfite free. However, even though some consumers consider wines without preservatives as more natural products, eliminating sulfites can reduce the quality of the wine because it is unstable and has much less aging potential. As a result, organic handling may be considered as inferior good. Producers of organic handling wine can obtain an organic handling certificate from the U.S. Department of Agriculture. It should be emphasized that different certification criteria varies across countries for "organic wine," so the above way of categorizing organic wine may not apply outside the United States. For example, in France and Italy, wines with added sulfites are allowed to be labeled as "organic handling wines," but they are only "organic grape wine" in the U.S. market.

The objective of this study is to investigate whether organic claims affect wine prices and whether they interact with other product characteristics. The article proceeds as follows: first, a brief review of relevant literature is presented. Then the theoretical basis of the analysis and the data set are presented. Following that, the estimation methodology and results are presented, and their implications discussed. Finally, concluding remarks are offered.

Literature Review

Identifying the determinants of wine prices using hedonic techniques is a well established approach in literature. Many attributes have influential impacts on wine prices, and there is no lack of work focused on this topic. Combris *et al*. (1997, 2000) utilized a hedonic price approach to analyze Bordeaux wines and found that market price is predominantly explained by objective characteristics (such as expert rating score and vintage), while sensory variables (such as tannins content and other measurable chemicals) are not statistically significant.

Wine rating scores by specialized magazines can act as signal to consumer and is shown to be significant by many researchers (see, for example, Oczkowski, 1994; Landon and Smith, 1997; Schamel and Anderson, 2003; Angulo *et al*., 2000), and therefore should be included in modeling wine prices. The region of production is typically significant factor in explaining prices. Noev (2005) analyzes the Bulgarian wine market and finds a significant regional reputation effect. A declining valuation of French wines with geographical appellation in the British market is examined by Steiner (2004). Aging of the wine is an important explanatory variable in hedonic analysis as well. Costanigro *et al*. (2007) show that aging exhibits different patterns of marginal returns across different price segments of the wine market. In the Bulgarian market, Noev (2005) finds the age of wine has a strong positive and significant impact on market prices for red wines but is insignificant for white wines.

Hedonic approaches are also applied to assess the effect of organic characteristics on other food products. Maguire *et al*. (2004) estimate the price premium associated with organic baby food using data collected from two U.S. cities and find that the organic price premium is generally equal to 30 to 40 per ounce. Stevens-Garmon *et al*. (2007) find that organic price premiums in the fresh produce market increased by 42% between 2001 and 2004 using A.C. Nielsen Homescan data. Organic potatoes command the highest percentage premium, and organic tomatoes are the most favored choice overall. According to shipment records of an organic marketing cooperative from 2003 to 2005, organic corn and soybean premiums exceeded 100% of the conventional prices, while organic premiums for wheat varieties averaged 85% (Heiman *et al*., 2008).

For other approaches to analyze organic effects, Zhang et al. (2008) use a generalized double hurdle model and actual retail-level data to investigate how the consumers' social economic characteristics related to the growth of the fresh organic produce market. In a study conducted by Grunert and Juhl (1995), they applied smallest space analysis, cluster and discriminant analysis, the explanatory power of values for environmental attitudes, and the relationships between attitudes and buying of organic foods to determine which values are relevant for environmentally concerned versus unconcerned consumer behavior. Gracia and de Magistris (2008) stated that consumers will choose the product (organic versus conventional) that possesses the combination of attributes that maximizes its utility and analyzed consumer's choice for *organic foods* is within the random utility discrete choice model and a bivariate probit model. They argued that greater information on *organic food* products is crucial to expand its demand in the South of Italy because this information will increase the consumer's *organic* knowledge.

Organic foods can claim price premium primarily because of consumer's attitudes towards these products or their beliefs of high quality of organic food. Magnusson et al. (2001) find that consumer's most important purchase criterion is good taste from a nation-wide survey, and the organic foods are perceived to be more expensive and healthier than conventionally produced alternatives. Davies et al. (1995) demonstrates that factors in organic food purchase are not necessarily related to environmental concerns: they include consumer's level of personal disposable income, presence of children and a predominant age-range. Tregear et al. (1994) point out that some purchasers of organic produce believe that the taste of the food was enhanced over conventionally grown products. In Zanoli and Naspetti's paper, they presented partial results from an Italian study on consumer perception and knowledge of organic food and related behavior. They found that even if organic products are perceived as difficult to find and expensive, most consumers judge them positively. Mann (2003) argues that subsidies for organic food may be justified by the concept of individualistic merit goods.

In the case of wine, there are some studies that focus on the consumer's response to environmental-friendly wine such as pesticides-free wine. Bazoche et al (2008) conducted an experiment to analyze how environmental friendly information affects wine consumer's willingness to pay. Their results show that consumers do not value the environmental effect alone. The certifier is also important. Loureiro (2003) estimates consumers' willingness to pay for geographical and environmental labels on Colorado wines. Her main finding is that environmentally friendly labeling in wine is an inefficient marketing tool for wines perceived to be of low quality. Also, there are studies trying to determining the premium consumers are willing to pay for organic wine. Mollá-Bauzáet al (2008), estimated the premium price that Spanish consumers are willing to pay for an organic wine with respect to the price of a conventional wine with similar characteristics by contingent valuation methods. The main findings show that consumers with a healthy life style are those willing to pay a higher price for an organic wine.

Although previous research is abundant on organic food products and hedonic price analyses of wine, even environmental aspects of wine, the two areas of inquiry have not intersected. The closest work is Delmas and Grant (2008), who examine eco-labeling and eco-certification in the context of wine industry. They find that eco-certification has a positive effect on wine prices, while eco-labeling has a negative effect. Delmas et al (2008), provide some background on organic and biodynamic practices in U.S. wine industry. They state that organic wine is a growing business but relatively small when compared to the larger wine industry. They find that the value of labeling organic or biodynamic is difficult to assess in wine because little is known about the potential benefits of sustainable practices on wine quality and health.

The gap in the economic literature on organic wine exists probably because the organic wine industry is still at its beginning stage. Most consumers are not familiar with the difference between organic wine and wine made from organically grown grapes. In Delmas and Grant's (2008) consumer survey, 66% of the 400 respondents were familiar with "organic wine" and 39% had tasted organic wine, only 19% were familiar with the difference between organic wine and organically grown grapes. Since the distinction between organic handling wine and wine made from organic grapes is not readily known, people might associate both with lower quality.

Theoretical Context

Following the standard hedonic price model (Rosen, 1974), the price of wine, P, is assumed to be described by a hedonic price function, $P = P(z)$, where z is a vector of attributes. The implicit price of an additional unit of a particular attribute can then be calculated as the partial derivative of the hedonic price function with respect to that particular attribute. Each consumer chooses an optimal bundle of attributes and all other goods in order to maximize utility subject to a budget constraint. For continuously varying attributes, the chosen bundle will place the consumer so that his or her indifference curve is tangent to the price gradient, $\partial P/\partial zj$, for each attribute.

Therefore, the marginal willingness to pay for a change in a wine attribute is equal to the derivative of the hedonic price function with respect to that attribute. Finite differences $\Delta P / \Delta Z_j$ represent marginal willingness to pay for discretely varying attributes.

Data

The data set is comprised of 12,821 observations California and Washington red wines, spanning 17 years (1991-2007). There are 633 observations of organic grape wines and 200 organic handling wines. We categorized the wine types by matching data all USDA National Organic Program certificated lists from California and Washington. We define a wine as organic grape wine if the wine is produced from vineyards or wineries that are USDA organically certificated for their grapes. For organic handling wines, the producers are certificated as organic handlers.[4] There are four continuous variables in the data set: (1) price, which is adjusted to the year 2000 by the consumer price index for alcohol, (2) rating score obtained from the expert sensory evaluation by the *Wine Spectator*, (3) the number of cases produced, and (4) the years of aging before commercialization. Indicator variables are used to denote macro-region of production, variety, and the presence of other label information such as “reserve”, “vineyard” and “estate produced.” The macro-regions of production for California wines include Napa Valley, Bay Area, Sonoma, South Coast, Carneros, Sierra-Foothills, Mendocino, and other California. Washington wines. Washington wines are not identified by region. These geographical partitions

[4] These two kinds of wines are not necessarily having organic label information on their bottles.

are those adopted by *Wine Spectator* to categorize wines. Varieties include Zinfandel, Pinot Noir, Cabernet Sauvignon, Merlot, and Syrah grapes, as well as wines made from blending of different varieties (non-varietals). The vintage year is available for each wine. Descriptive statistics for these variables are reported in Table 1.

Empirical Methodology

Economic theory often suggests the expected sign of the partial derivatives of price with respect to specific attributes but does not restrict functional form. Nevertheless, the choice of the functional form in the hedonic model is fundamental since it determines how the marginal prices will be functionally related to the attributes. Triplett (2004) argued that model specification is ultimately an empirical matter. Given the uncertainty surrounding the correct specification, a flexible functional form is arguably a prudent empirical modeling strategy. Box-Cox transformations are applied to choose a functional form, and the results show that the most appropriate form of the dependent variable in the hedonic function is the -0.25 power transformation of price. We also allow for non-linearity in score and aging by including a quadratic term. We centered these two variables by subtracting their means. This transformation because when adding squares term of an independent variable to the right side of the equation will induce linear dependence problem among predictors. Standardizing by its mean can reduce this multicollinearity.

Therefore, the following functional form is selected:

$$
\begin{aligned}
price^{-0.25} = {} & \beta_0 + \beta_1(\text{Score}) + \beta_2(\text{Score})^2 + \beta_3(\text{Age}) + \beta_4(\text{Age})^2 \\
& + \beta_5 \ln(\text{Cases}) + \sum_{i=1}^{8} \beta_{5+i}(\text{Region}_i) + \sum_{i=1}^{5} \beta_{13+i}(\text{Variety}_i) \qquad (1) \\
& + \sum_{i=1}^{3} \beta_{18+i}(\text{Label}_i) + \sum_{i=1}^{9} \beta_{21+i}(\text{Vintage}_i) + \beta_{31}(\text{OG}) + \\
& \beta_{32}(\text{OH}) + \beta_{33}(\text{OG*ES}) + \varepsilon_i
\end{aligned}
$$

Where *Score* is the rating score, *Age* represents years of aging before commercialization. The variable *Cases* represents the number of cases produced. The natural log of this variable provides the best fit. *Region* indicates one of eight regions of production. *Other California* is excluded (benchmark) category. *Variety* indicates grape variety. The omitted variety is Zinfandel. *Label* includes three variables. The variable *Reserve* indicates the word "Reserve" is reported on the label; *Vineyard* indicates that a specific vineyard's name is on the label, and *Estate* indicates estate-produced wine. *Vintage* is the year of production. The variable OG indicates organic grape certification, and OH indicates organic handling wine. The variable ES indicates the presence of "estate grown" on the label information.

The model is estimated via ordinary least squares (OLS). Breusch-Pagan-Godfrey Tests indicate a moderate degree of heteroskedasticity, but the possible gains in estimation efficiency that might be achieved by adjusting the estimator for an appropriate heteroskedastic process are muted by the consistency of the OLS estimator and the large sample size. Nevertheless, to address this concern, the covariance matrix of the parameters was estimated using White's consistent heteroskedasticity-robust estimator. Although the sample sizes are limited, the

Breusch-Pagan-Godfrey tests show that heteroskedasticity is not a significant concern, and we can proceed to estimation by OLS.

Results and Discussions

Estimation results are presented in Table 3. The parameters of greatest interest are those indicating organic grape wines (OG), organic handling wines (OH), and the interaction between organic grape and estate (OG*ES). From the results, organic grape wines characteristic has a positive effect[5] on price but only at the 11% level of statistical significance. Organic handling characteristic is negative and significant at the 1% level. This result confirms our *a priori* expectation: organic grape wines are considered as higher quality wines, but organic handling wines are perceived by many as negative. Examination of additional estimated hedonic function coefficients and corresponding implicit prices serves to further characterize organic grape wines and organic handling wines. The estimated implicit prices associated with organic grape wine (*OG*) and organic handling (*OH*) are 0.7096 and -9.6093, respectively. Therefore, organic grape wines, on average, command $0.71 (2.27%) price premium, while organic handling products, on average, sell for $9.61 (30.74%) less.

It seems strange that there will be wine producers making organic handling wine given it has such disadvantage on selling price. But actually, it can happen. First, some people really truly believe in organic process of wine producing. For these kind of people, organic method is what

[5] Note that owing to the functional form used, a negative coefficient results in a positive implicit price.

they care. Second, a lot of consumers are confused between organic grape wine and organic handling wine. Therefore, organic handling wine might be sold very well at the low price. Third, lower price does not necessarily mean lower profit. Production cost and sales volume are also important factors.

The interaction term *OG*x*ES* represents organic grape wine that is estate grown (i.e. grown at the winery). This term has a significant positive effect on price. Furthermore, from the comparison of this estimate to the one associated with the coefficient for organic grape indicator variable, the value is an order of magnitude larger and highly statistically significant. This result suggests that while using organic grapes has a limited effect on price, the combination of using organic grapes that are grown on one's own property can boost price premium. A possible explanation behind this result is that consumer who buy organic view estate-grown organic grapes as more authentic. This argument is related to ideas about trust. Organic consumers may consider the label information "estate" in combination with organic grapes as a signal of true organic product, and therefore are willing to pay the price premium generated by this kind of characteristic.

The other results are consistent previous findings. Price increases with rating score and aging over the range of the data and decreases in the number of cases produced. Regional appellations have price premium relative to a generic California wine with Napa Valley commanding the largest premium. Coefficients associated with variety variables capture the difference in price relative to Zinfandel grapes and the coefficients for vintages refer to price differences relative to the excluded year 2006.

From the results, organic grape wine can command a price premium. However, whether a winery should turn into organic growing still remains a question. The objective of most wineries is maximizing profit. Therefore, higher selling price is just one side story; production cost is also an important factor. By introducing organic grapes in wine producing, there will be increases in cost. According to Silverman, L., (2003), switching from conventional to organic certified winery can add up 10 to 15 percent in cost for the first three to four years. This is so because growing and harvesting organic grapes cost more, and the winery also needs to pay overhead cost for administration, equipment, organic certification, etc. Another caution about choosing to make organic grape wine is production risk. This kind of risk is not only from crop perception; policy changes may also induce higher risk, especially when the winery is in another country to avoid higher producing cost.

Conclusions

From interpreting estimation results and computing implicit prices for each factor, we have a deeper understanding about the economics of organic grape wines and organic handling wines. First, organic grape wines command a premium that is not statistically different from zero. However, this is in contract to the discount that is needed to sell organic handling wines, suggesting that they are inferior products. Moreover, organic grape wine whose label information contains “estate” can command a significant price premium.

These findings can be quite valuable to wine producers and wine industry. First, it confirms the intuition that organic grape wine is considered to be a more quality product. Wine producers who are thinking about transitioning their vineyards to organic can be reassured that organic grape wine can claim price premium if they produce estate grown wines. But joining organic classification still needs more considerations because of the new cost induced by it.

References

Angulo, A.M., J.M. Gil, A. Gracia and M. Sanchez. (2000). "Hedonic Prices for Spanish Red Quality Wine," *British Food Journal,* 102(7):481-493.

Bazoche, P., Deola, C., and Soler, L.G. (2008) "An experimental Study of Wine Consumers' Willingness to Pay for Environmental Characteristics," *12th Congress of the European Association of Agricultural Economists – EAAE 2008.*

Combris, P., Lecocq, S., and Visser, M. (1997). Estimation of a hedonic price equation for Bordeaux wine: Does quality matter? *Economic Journal,* 107: 390-402.

Combris, P. and S. Lecocq and M. Visser. (2000). "Estimation of a Hedonic Price Equation for Burgundy Wine," *Applied Economics* 32:961-967.

Costanigro, Marco, McCluskey, JillJ. and Mittelhammer, Ron C. (2007). "Segmenting the Wine Market Based on Price: Hedonic Regression when Different Prices mean Different Products", *Journal of Agricultural Economics*, 58(3), 454-466.

Davies, A., Titterington, A.J., and Cochrane, C. (1995). "Who buys organic food? A profile of purchasers of organic food in Northern Ireland." *British Food Journal*, 97: 17-23.

Delmas, M. and Grant, L. (2008) "Eco-labeling Strategies: The Eco-premium Puzzle in the Wine Industry", AAWE working paper NO.13

Delmas, M., Doctori-Blass, V. and Shuster, K. (2008) "Ceago Vinegarden: How green is your wine? Environmental differentiation strategy through Eco-labels", AAWE working paper NO.14

Gracia, A., de Magistris, T., (2008), "The Demand for Organic Foods in the South of Italy: A Discrete Choice Model", *Food Policy*, October 2008, v. 33, iss. 5, pp. 386-96

Grunert, S., Juhl, HJ., (1995), "Values, Environmental Attitudes, and Buying of Organic Foods", *Journal of Economic Psychology*, March 1995, v. 16, iss. 1, pp. 39-62

Heiman, R. and Peterson, H. (2008) "Determinants of Premiums Received by Organic Field Crop Producers", *Review of Agricultural Economics*, Volume 30, Number 4, Winter 2008 , pp. 729-749(21)

Landon, S. and C.E. Smith. (1997). “The Use of Quality and Reputation Indicators by the Consumers: The Case of Bordeaux Wine,” *Journal of Consumer Policy,* 20:289- 323.

Loureiro, ML., “Rethinking new wines: implications of local and environmentally friendly labels”, *Food Policy*, 28 (2003) 547–560

Magnusson, M.K., Arvola, A., Koivisto Hursti, U.-K., Aberg, L., and Sjoden, P.o. (2001). Attitudes towards organic foods among Swedish consumers. *British Food Journal,* 103: 209-227.

Maguire, KB. , Owens, N., and Simon, NB. (2004). “The Price Premium for Organic Babyfood: A Hedonic Analysis”, *Journal of Agricultural and Resource Economics,* 29 (1) : 132 - 149

Mann, S., (2003), “Why *Organic Food* in Germany Is a Merit Good”, Food Policy, October-December 2003, v. 28, iss. 5-6, pp. 459-69

Mollá-Bauzá, M.B., Martínez, L., Poveda, A.M., Pérez, M.R., (2005), “Determination of the surplus that consumers are willing to pay for an organic wine”, *Spanish Journal of Agricultural Research*, 3(1), 43-51

Noev, N. (2005). "Wine Quality and Regional Reputation: Hedonic Analysis of the Bulgarian Wine Market," *Eastern European Economics*, Volume 43, Number 6, 5-30

Oczkowski, E. (1994). "Hedonic Wine Price Function for Australian Premium Table Wine," *Australian Journal of Agricultural Economics*, 38:93-110.

Schamel, G. and K. Anderson. (2003). "Wine Quality and Varietal, Regional and Winery Reputations: Hedonic prices for Australia and New Zealand ," *Economic Record,* 79 : 246.

Silverman, L., (2003), Benziger Family Winery Case Study

Steiner, B. (2004). "French Wines on the Decline? Econometric Evidence from Britain," *Journal of Agricultural Economics,* 55(2):267-88.

Stevens-Garmon, J., Huang, C. L., Lin, B. H., (2007). Organic demand: a profile of consumers in the fresh produce market. *Choices* 22, 109–115.

Tregear, A., Dents, J.B., and McGregor, M.J. (1994). The demand for organically grown produce. *British Food Journal*, 96: 21-25.

Zanoli, R., and Naspetti, S., (2002), "Consumer motivations in the purchase of organic food: A means - end approach." *British Food Journal.* Volume 104, Issue 8, Page 643 – 653

Zhang, F., Huang C L., Lin, BH., Epperson, JE., (2008) Modeling Fresh Organic Produce Consumption with Scanner Data: A Generalized Double Hurdle Model Approach, *Agribusiness*, Autumn 2008, v. 24, iss. 4, pp. 510-22

Table 3.1 Short Descriptions and Abbreviations of Variables

Variables	Short Description	Binary/Non-binary
Scscore	Standardized Rating Score from Wine Spectator	Non-binary
Scscore2	Square of Scscore	Non-binary
Agesc	Standardized Years of Aging Before Commercialization	Non-binary
Agesc2	Square of Agesc	Non-binary
Lncs	Ln term of Number of Cases Produced	Non-binary
Napa BayCentral Sonoma SouthCoast Carneros SierraFoothills Mendocino Washington	Regions of Production	Binary
Nonvarietal Pinotnoir Cabernet Merlot Syrah	Grape Variety	Binary
Reserve	Patronage Information: "Reserve"	
Vineyard	Patronage Information: Specific Name of the Vineyard	Binary
Estate	Patronage Information: "Estate" Produced Wine	
y91, y92,…,y05	Vintage	Binary
OG	Organic Grape Wine, decided by organic crop certificate	
OH	Organic Handling Wine, decided by organic handling certificate	Binary
OG*ES	Interaction between Organic Grape and Estate	

Table 3.2 Descriptive statistics of the non-binary variables by sub-sample

Descriptive Statistics

Wine		Price	Case	Score	Age
Not Organic Grape/Handling Wine (N = 11988)	Mean	31.30	6610.92	86.31	2.78
	Min	5.15	16	60	1
	25 quartile	16.86	477	84	2
	Median	23.61	1,200	87	3
	75 quartile	34.09	3,700	88	3
	Max	1,844	950,000	99	9
	Std.	46.76	27,201.55	3.86	0.74
Organic Grape Wine (N = 633)	Mean	34.36	2,306.23	85.60	2.77
	Min	6.92	50	68	1
	25 quartile	19.62	460	83	2
	Median	27.90	973	86	3
	75 quartile	38.18	2,400	88	3
	Max	184.05	55,000	96	11
	Std.	25.09	4,589.81	3.97	0.82
Organic Handling Wine (N = 200)	Mean	19.16	49,025.62	87.46	3.01
	Min	6.54	20	74	1
	25 quartile	10.47	1,000	86	3
	Median	18.77	4,638	88	3
	75 quartile	26.43	42,000	90	3
	Max	61.88	550,000	93	5
	Std.	10.06	91,701.63	3.00	0.69

* CPI adjusted to 2000

Table 3.3 Estimation results from All Wines Model

Variables	Estimates	Std.dev	P-value
Intercept	0.4139	39.2652	0.0000
Score	-0.0071	-59.9071	0.0000
Score2	-0.0004	-24.1917	0.0000
Age	-0.0117	-20.8526	0.0000
Age2	0.0007	2.4878	0.0064
Ln_cases	0.0124	48.8655	0.0000
Napa	-0.0534	-33.8569	0.0000
BayCentral	-0.0316	-15.2630	0.0000
Sonoma	-0.0351	-23.3934	0.0000
SouthCoast	-0.0254	-15.1555	0.0000
Carneros	-0.0376	-19.6693	0.0000
SierraFoothills	-0.0174	-7.4639	0.0000
Mendocino	-0.0156	-8.1556	0.0000
Washington	-0.0029	-1.5741	0.0577
Nonvarietal	-0.0415	-24.5209	0.0000
Pinotnoir	-0.0346	-32.5220	0.0000
Cabernet	-0.0307	-28.6616	0.0000
Merlot	-0.0254	-24.2363	0.0000
Syrah	-0.0077	-5.6271	0.0000
Reserve	-0.0110	-10.5454	0.0000
Vineyard	-0.0082	-9.9989	0.0000
Estate	-0.0056	-2.4240	0.0077
y91	0.0396	3.8599	0.0001
y92	0.0412	4.0211	0.0000
y93	0.0316	3.0914	0.0010
y94	0.0269	2.6347	0.0042
y95	0.0173	1.6917	0.0454
y96	0.0095	0.9305	0.1761
y97	0.0031	0.3022	0.3812
y98	-0.0089	-0.8689	0.1925
y99	-0.0032	-0.3173	0.3755
y00	-0.0080	-0.7836	0.2166
y01	-0.0011	-0.0984	0.4608
y02	-0.0089	-0.7723	0.2200
y03	-0.0092	-0.7557	0.2249
y04	-0.0024	-0.2136	0.4154
y05	-0.0046	-0.4154	0.3389
OG	-0.0024	-1.1896	0.1171
OH	0.0325	10.2382	0.0000
OG*ES	-0.0279	-3.5405	0.0002

CHAPTER FOUR

THE VALUE OF GOOD NEIGHBORS: A SPATIAL ANALYSIS OF THE CALIFORNIA AND WASHINGTON WINE INDUSTRIES

Chapter Abstract: The fact that wineries tend to cluster in certain sub-regions can be partially explained by the terroir of those areas. However, a gap in our understanding of the spatial relationships among wineries remains. In this article, winery-level data with geographic information system (GIS) coordinates are utilized to examine the spatial relationships among neighboring wineries. Spatial effects for the California and Washington wine industries are assessed by performing clustering tests based on wine prices and tasting scores. A spatial lag model is then estimated to test the hypothesis that there are positive effects from neighbors when analyzing the hedonic price equations. The regression results indicate that there exists strong and positive neighbor effect.

Key words: GIS, clustering, spatial lag model, wine

Introduction

One bad wine in the valley is bad for every winery in the valley. One good wine in the valley is good for everyone. --Robert Mondavi on the Napa Valley in the 1960s (Stiler, 2007).

When one examines a map with points indicating winery locations in California and Washington State, there is an interesting phenomenon. Wineries are intensively located in some of the areas but almost none of them in others. In other words, most of the wineries choose to locate close to each other. The obvious reason for this location pattern is probably because of geographic features as defined by American Viticultural Area: the *terroir* of some regions is more suitable for grape growing. Therefore, wineries prefer to select a location that can explore this resource advantage. However, the reason that wineries do not evenly distribute within grape growing region but choose to cluster together cannot be well explained by *terroir*. Therefore, a research question comes out naturally. Do wineries benefit from choosing locations that are in close proximity to high reputation neighbor wineries?

Many studies on wine markets have considered location as factor, but geographic clustering and neighborhood effects (micro-level interactions among wineries) in wine industry have not been fully analyzed. The idea behind Tobler's "First Law of Geography," is that everything is related to everything else, but close things are more related than distance things (Tobler 1970). Following this idea, the influence from neighbors may be quite important to a winery's product prices.

Possible reasons for winery concentrations can come from both the producer and consumer points of view. First, from production side, spatial heteroscedasticity and spatial dependence can be the reasons. Spatial heteroscedasticity refers to the *terroir* of a sub-region. It is an exogenous factor. Since a winery and its neighbors share the same grape growing conditions, it is possible that their products exhibit some degree of similarity in terms of their characteristics. This may result in similar tasting scores from wine experts, and many previous studies indicate that score is the most important factor in determining a wine's price. Spatial dependence represents the spillover effects of reputation and management among wineries, which are located in close proximity. This is an endogenous factor: nearby wineries usually are located in the same appellation, which serves as a reputation signal to the market. Also, knowledge about how to make wine is easier to be communicated. Therefore, closeby wineries are able to and willing to charge a similar price for their products.

Second, from consumer's side, perceptions about wines coming from the same area tend to be the similar, so it is more likely for consumer to be willing to pay similar price for wines from the same micro-region. For example, if a winery with a reputation for producing extremely high quality wine is located close to another winery, consumers might consider the neighboring winery to also have high quality products. Therefore, we cannot ignore the impacts from neighbors of a winery.

According to Can (1998), spatial analysis is usually divided into two stages. The first stage is the exploratory spatial data analysis (ESDA) stage or spatial pattern identification stage, which concerns description rather than explanation. The second stage is called confirmatory data analysis (CDA) stage, which involves modeling the impact of spatial structure on behavior and outcomes in addition to economic considerations. In this study, we will follow this framework to analyze the spatial effects for Washington and California wine industries by first performing clustering tests based on prices and tasting scores and then formally measuring neighborhood effects via a spatial lag model.

Porter (2000) is the seminal article in the literature on geographic clustering analyses. Porter explains the literature and methods for clusters, or geographic concentrations of interconnected companies, and their role in competition and other implications. He argues that clusters represent a new way of thinking about economics, and they necessitate new roles for companies, government, and other institutions in enhancing competitiveness. For the identification of clusters, he indicates that the ultimate determining factors of a cluster are the strength of the "spillovers." The geographic scope of a cluster is related to distance, and informational, transactional and other efficiencies occur over the cluster. He also argues that all existing and emerging clusters deserve attention. From an empirical point of view, Jaffe *et al*. (1993) uses patent citations to test whether the knowledge spillovers are geographically localized. They find that localization does exist and it slowly fades over time. However, no previous studies have focused on geographical clustering of wine and its effects. Other types of clustering analysis has been a major topic for some studies. Costanigro *et al*. (2009) identify wine segments for Washington and California wines with a procedure called local polynomial regression clustering, which is clustering by local regression coefficients, but Geographic Information System (GIS) data was not used. Kaye-Blake *et al*. (2007) utilize cluster analysis on potential market segments for genetically modified food. However, their clusters are based on survey responses.

For modeling spatial effects, Anselin (1999) summarizes the foundation and regression issues of spatial models. In the applications of spatial model, Wu and Hendrick (2009) estimate a spatial lag reaction function for property tax rate of Florida municipal governments in 2000 and 2004 and compare model fitness as well as results from different specifications of spatial relationships. Garretsen and Peeters (2009) test the relevance of spatial linkages for Dutch (outbound) foreign direct investment (FDI). They estimate a spatial lag model for Dutch FDI to 18 host countries and find that third-country effects matter.

GIS can be a helpful and powerful tool in spatial relationship studies. As indicated by Can (1998), GIS enables the researcher to organize, visualize, and analyze data in a map form, provides the medium for the integration of multiple geographical data sets, and gives analytical support for spatial data analysis by providing explicit information of spatial relationships. Wallsten (2001) applies GIS and firm-level data to explore agglomeration and spillovers at the firm level over discrete distances. He finds that the number of other firms participating in Small Business Innovation Research (SBIR) program within a fraction of a mile predicted whether a firm wins awards.

In this chapter, winery-level GIS data is collected to describe the spatial relationships among wineries for California and Washington State wine industries. First, we conduct formal statistical tests to decide whether there exists geographic winery clusters based on price and tasting score. Second, a spatial lag model is applied to test the hypothesis that there is positive effect from neighbors when analyzing the hedonic relationships among price and other factors. Analyses are done for both California and Washington State.

Spatial analyses of California and Washington State wine industry can improve the understanding of the economic relationships among wine's price and product's attributes. All previous studies about Washington and California wine industries either ignore the spatial autocorrelations among wineries or wine regions, or treat them as nuisance and incorporate them into the error structure of the regression model. However, there is a high possibility that spatial autocorrelations (spatial effects), which may be the results of spatial interaction processes, externalities, spillover and so on, is significantly present among Washington and California wineries. If we ignore the spatial nature of the data, it may lead to biased or inefficient estimates and misleading inference (Anselin, 1988). Consequently, this research can help to look for a more appropriate econometric model to describe the relationships among price and other characteristics of Washington and California red wines, when considering the spatial effects from the distribution of hundreds of existing wineries.

The rest of this chapter proceeds as following: First, we will describe the data used in this study. Second, we will introduce the econometric methods and model applied in this study, and the statistics test for geographic clustering. Following these are the results and discussion. Last, we offer conclusions.

Data

The data set consists of winery-level data from two States: Washington and California.

For each observation, information about price, rating score, case, year of aging, vintage and production region is collected from *Wine Spectator* magazine (online version). Since the observed unit in this study is individual winery, the above variables of price, score, case and age are averaged across grape varieties[6] and vintages[7] for every winery in our data set. Indicator variables are used to denote the winery's production area, representing collective reputations. The regions for California wines include Napa Valley, Bay Area, Sonoma, South Coast, Carneros, Sierra-Foothills, Mendocino and other California. In Washington, they are Columbia Valley, Yakima Valley, Walla Walla Valley, Puget Sound and other Washington.

For Washington State, information about 79 wineries is gathered. For California, there are 876 wineries in our data set. Table 1 reports the descriptive summary of non-binary variables in our data set and Table 2 provides short descriptions and abbreviations of all variables used in the empirical analyses.

To describe the spatial property of each winery, we incorporate GIS data into our study. Each winery contains a name, street address, city, state and zip code. The street address in the data allows us to recover each winery's exact longitude and latitude coordinates by geocoding address in GIS program[8]. Following geocoding, we can obtain an accurate understanding of almost any

[6] This study only takes red wines into concern; the grape varieties are Zinfandel, Pinot Noir, Cabernet Sauvignon, Merlot, Syrah grapes, and wines made from blending of different varieties (non-varietals).

[7] The vintages are from 1991 to 2000.

[8] The data set originally contains 137 wineries for Washington and 1195 for California. However, due to the difficulty of finding street address (e.g. some wineries only provide P.O. box or can only locate to city), and GIS's limited ability

spatial relationship among wineries in our data set, such as pairwise distances between any two wineries and the nearest *K* neighbors for any selected winery. Also, we are able to obtain a visual understanding about the spatial distribution of wineries in both Washington and California. Figures 1 and 2 are winery distribution for Washington and California, respectively.

About the spatial information of our data set, two things need to be mentioned. First, wine Spectator is the only source of our data set. We only include wineries whose wines are listed in Wine Spectator. Second, among all the wineries, in Washington State, 10.13% of them are estate wineries and 4.57% are estate wineries in California. Only these wineries use their own grapes to produce wine instead of buying them from external growers. The coordinate of each winery is where the producing processes take place.

Method and Model

There are two distinct ways to model spatial dependence: as an additional regressor in the form of a spatially lagged dependent variable (Wy), or in the error structure (E $[\varepsilon_i \varepsilon_j] \neq 0$). The former one is referred as a spatial lag model and has the form of $y = \rho Wy + X\beta + \varepsilon$, and the later one is usually called spatial error model with the expression $y = X\beta + \varepsilon$ and $\varepsilon = \lambda W\varepsilon + u$. The choice of the model depends on the research interest. When the focus of interest is to assess the existence and strength of spatial interaction, the spatial lag model is more appropriate, since it

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to locate some addresses, only 79 wineries from Washington and 876 wineries from California can be applied in the study.

interprets the spatial dependence in a substantive form. However, when the concern is to correct the potentially biasing influence of the spatial autocorrelation due to spatial data, the spatial error model is appropriate to meet the goal (Anselin 1988).

The prior objective in this study is to model spatial effects in California and Washington State wine industries. Therefore, it is necessary to include a specific term of neighborhood effect in the explanatory variables, and the spatial lag model will be a reasonable choice.

Regarding other explanatory variables, we choose to include factors showing significant effects in many previous hedonic analyses of wine. Therefore, the formal expression of our spatial lag model is

$$\begin{aligned} \text{f(Price)} = {} & \rho W(f(\text{Price})) + \beta_0 + \beta_1(\text{Score}) + \beta_2(\text{Case}) + \beta_3(\text{Age}) \\ & + \sum_{i=1}^{j} \beta_{3+i}(\text{Region}_i) + \varepsilon \end{aligned} \tag{1}$$

Where ρ is a spatial autoregressive coefficient, *W* is the spatial weight matrix that will be specified later. *Score* is the rating score from *Wine Spectator* magazine, *Case* is the number of cases produced by the winery, and *Age* represents years of aging before commercialization. All of these three variables are averaged values for the particular winery across the observation period. *Region* tells us the place of production and each area is represented by an indicator variable. For Washington State, there are four regions (*j* is equal to four). The regions are the Columbia Valley, Yakima Valley, Walla Walla Valley and Puget Sound. For California, there are seven macro regions (j = 7). They are Napa Valley, Bay Area, Sonoma, South Coast, Carneros, Sierra-Foothills and Mendocino are the seven production regions. Since for both states, the region variables exclude Other Washington or Other California, parameter before each of them indicates the difference between wine from this area and a generic Washington or California wine.

The form of the dependent variable *f(Price)* is determined by a Box-Cox transformation. For Washington State, we use *ln(Price)* as our final dependent variable in the regression, while for California, the best transformation is $Price^{-0.25}$. Equation (1) is estimated via spatial econometrics method.[9]

The specification of spatial weight matrix in spatial econometric analysis is important and influential to regression results. In previous studies, Frizado *et al*. (2009) emphasize the sensitivity of spatial weights matrix selection to the cluster identification results by Local Moran's and Getis-Ord Gi when concerning U.S. county size. They conclude that the selection of spatial weighting methodology should depend on the study's purpose, the distribution of county sizes, and the industry being studied. Also, Anselin (1999) points out that the elements of the weights matrix are non-stochastic and exogenous to the model. Typically, they are based on the geographic arrangement of the observations, or contiguity. Several forms of spatial weights are analyzed in literature, such as inverse distance or inverse distance squared (Anselin, 1980), structure of a social network (Doreian, 1980), economic distance (Case, Rosen and Hines,1993) and K nearest neighbors (Pinkse and Slade, 1998).

However, the specification of spatial weights is not arbitrary. The range of

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[9] See Anselin (1988)

dependence allowed by the structure of W must be constrained. Therefore, the key question in every spatial econometric analysis is how to define the range of the neighborhood. Intuitively, if the units all belong to one cluster, then distance decay will be a reasonable choice of spatial weights because it treats all units as neighbors. However, when units are distributed as several “hot spots” in space, only consider distance weight will not be a good candidate. Since treating a far-away point, which belongs to another cluster, as neighbor does not make sense. Also, to avoid confusing the exogeneity of weights, deriving weights geographically is more appropriate.

Therefore, based on the geographic distribution of California and Washington State wineries, we select K nearest neighbors[10] as the structure of our spatial weight matrix. As the empirical standard of model selection, we also compare Akaike's Information Criterion (AIC) of models with different spatial weight matrix and find that the *K* nearest neighbors structure that results in the best AIC value. The AIC measurements have also been applied in a number of spatial analyses as mentioned in Anselin (1988, page 247).

Clustering Test (Global Moran’s I)

Before proceeding to the spatial econometric analysis, it is necessary to get an approximate idea of how well the geographic connection is among wineries. Formal measurement of trends in spatial pattern can be accomplished by spatial association (or autocorrelation) statistics. The most common one to identify geographic cluster is Moran’s I statistic, which is derived from a

[10] Only the nearest K wineries are considered to have influence on the interest winery.

statistic developed by Moran (1948, 1950a, 1950b). Also there are Geary's c, Gamma, Gi and Gi* as summarized by Anselin (1998). In the literature, geographic cluster analysis is widely applied in housing market. Anselin and Can (1995) use an exploratory spatial approach to the examination of spatial structure in 1990 mortgage originations for Dade County, Florida. They apply local spatial association statistics to identify areas that exhibit statistically significant clustering of high and low levels of mortgage activity (i.e., "hot spots").

In this study, we are interested in testing the general connection among all wineries from a State. Therefore, to evaluate whether wineries' spatial distribution pattern expresses clustered, dispersed, or random, Global Moran's I statistics is appropriate. Also, geographic connection can be based on many aspects; the ones we choose in this study are wine's price and rating score.

Global Moran' I statistics is defined as

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2} \tag{2}$$

where N is the number of spatial units indexed by i and j; X is the variable of interest, here is wine's price premium; $\bar{X}$ is the mean of X, or the mean of price premium; and w_{ij} is a matrix of spatial weights, which are defined by K nearest neighbors criteria.

Values of Global Moran's I range from -1 (indicating perfect dispersion) to +1 (perfect clustering). Inference for Global Moran's I is based on a normal approximation. The Z-score value is calculated to decide whether to reject the null hypothesis that there is no spatial clustering. If the threshold significance level is set at 0.05, then a Z score would have to be less than –1.96 or greater than 1.96 to be statistically significant.

For this study, the results from Global Moran's I tests of price and score for Washington State and California are showed in Table 3 and 4. The *K* nearest neighbors spatial weight matrix is in use, and *K* is from 1 to 5 for Washington and between the range of 1 to 65 for California. The way to decide number of *K* will be discussed later. From the results, no matter how many neighbored wineries are considered, both price and score exhibit positive clustering distribution at the global level. Also, by comparing the Moran's I values, price clustering is stronger than score clustering.

A Global Moran's I test can be considered as a spatial pattern identification test. From the results, we can obtain a general understanding about the degree of spatial connection among winery's product price and quality (represent by tasting score) for both States.

Results and Discussions

Estimation results are presented in Table 5 and Table 6 for Washington State and California, respectively. Results are reported based on the choice of spatial weight matrix. The parameter ρ represents the degree of spatial effect among wineries. The probability values for each estimate are in parenthesis. For ease of comparison, we also provide estimation results from hedonic model without spatial lag term. They are presented in the last column of each table.

In the last row of Table 5 and 6, we compare the models based on their AIC. The model with the smallest AIC is highlighted. Also, three statistical tests (Wald, Likelihood Ratio and Lagrange Multiplier tests) are conducted to evaluate the hypothesis that there is no significant spatial effect among wineries within a state.

Washington State

For Washington State, we consider the nearest neighbors to be the closest 1 to 5 wineries. Therefore, K is less or equal to 5 in the spatial weight matrix. The reason for considering K in this range is that the AIC values a minimum point at $K = 3$ in this range. Three wineries represent about 4% of the total wineries that are listed for Washington state in the *Wine Spectator* ratings data base. There are only 79 observations for Washington State. From the results, we can see that regardless how many wineries are considered to be neighbors or potential candidates for spatial effects (from 1 to 5), according to the Wald, Likelihood Ratio, and Lagrange Multiplier tests, ρ is highly significantly different from zero and has a positive sign[11]. Since from the model specification, ρ is the parameter describing spatial correlation, this result indicates that neighbors do have significant and positive effect on a winery's own product price. Therefore, good neighbors can have beneficial impact to a winery, or we may say that there are positive neighborhood effects among Washington State wineries. This finding is consistent with positive

[11] Except "nearest 1 neighbor" is significant at 0.1 level or insignificant in LM test, others are at 0.01 level.

spillover theory, and it can be important to potential investors who are interested in developing new wineries in Washington State.

The AIC is used as the criteria for model selection. For Washington State, the three nearest neighbors spatial structure performs best with the smallest AIC of 15.6105. Consequently, in the following discussion, the results we refer to are from this model. For hedonic regression estimates, we obtain similar results as previous studies. *Score* has significant positive effect on price, indicating that expert evaluations have important influence on wine price. *Case* has significant negative impact on price, which is consistent with supply-demand theory: massive production may reduce price. *Age* affects price positively, which means that as the year of aging increasing, wine's value increases. For region dummy variables, all of them except *Columbia Valley*[12] are insignificant. Therefore, for the most cases, regional difference is not obviously present in Washington State wine industry, and this is probably the reason why people usually do not refer to micro wine production region for Washington State as do when they refer to California wine appellations.

Comparing the estimation results from the spatial model to hedonic regression results without considering spatial effects (Column 4 and Column 7 in Table 5); we see that there are not many differences. However, it is still necessary to consider spatial effects when conducting hedonic analyses, because from the comparison of AIC[13], model with spatial term is an improvement of simply hedonic regression.

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[12] Wines from Columbia Valley generate discount comparing to other Washington red wines.

[13] The AIC of hedonic model without spatial lag for Washington is 19.73.

California

For California, in the spatial weight matrices, we consider the number of significant nearest neighbors K to be between 1 and 65. We expect for the number of wineries considered as neighbors is much greater than that of Washington State because California has more wineries and the distance between wineries are generally smaller. In our data set, there are 876 wineries in the *Wine Spectator* ratings data base for California. Therefore, the number of wineries within a given area is greater compared to Washington, and a winery is likely to have more neighbors that may have potential spatial dependence. We find that the AIC statistic decreases and reaches its minimum when 35 wineries are considered as neighbors, which is also about 4% of the total wineries. After that, the value of AIC is fairly stable.

From the estimates of spatial lag parameter ρ together with the Wald, LR and LM tests, we find that good neighbors have significant and positive effects on winery's product price in California. Further, if we compare this positive spatial effect to its counterpart in Washington State, it shows that wineries in California may experience a more apparent neighborhood impact, because the probability values of spatial term estimates are all close to zero. This is the case because California has a much longer history and more established reputation for producing wine. The nature resources of grape growing are almost fully explored by wine investors, the intensity of wineries within a small sub-region is much greater than that of Washington State. Therefore, the connections among those close wineries are stronger due to this smaller distance between each others.

Among the K nearest neighbors spatial models we estimated for California, the model considering 35 nearest neighbors has the best AIC of -3173.595. Comparing this "best" nearest neighbor number to Washington State, where smallest AIC comes from the 3 nearest neighbors model, we may conclude that the good neighbor impact is more inclusive for California since a lot of surrounding neighbors of a winery can provide potential benefits. The following results discussions are based this model.

Since the dependent variable is the -0.25 power transformation of price, a negative sign for parameter estimate indicates a positive marginal effect on price. From the results, we can see that there are similar parameter estimates for the common factors on wine price in California as for Washington State: *Score* and *Age* have positive effect, while *Case* affects price negatively. All of the three variables are significant. However, for macro regions, except *SierraFoothills*, all other regions have significant price premium comparing to generic California red wines. This finding shows that micro region differences are present in California and is consistent with consumer's perception of the area.

Also, by comparing the spatial model to usual hedonic model, parameter estimates are not so much different. However, the spatial model is better according to AIC criteria. The AIC of the hedonic model without spatial term for California is -3124.117, which is greater than the AIC for all other spatial models in this study.

Further discussions about results

Two interesting points deserve more deep discussions: (1) Tradeoff between price and cost, (2) Long run effects from spatial correlation. First, spatial estimations for both Washington State and California suggest that clustering exists and positively affects price. These findings support the spillover effects from knowledge and reputation. However, for an entrepreneur who wants to start a new winery, this does not necessarily mean choosing the location right next to a high reputation winery is the best strategy and will generate maximum profit. There is a tradeoff between higher product price and greater cost. The land next to high reputation winery may have the opportunity of higher wine price, but it is likely that the added value is captured by the land. On the other hand, selecting land away from neighbors may cost much less and leave the new firm money to invest in other quality-affecting production factors. This study only focuses on the market price but not producing cost. Consequently, one cannot conclude that locating nearby a high reputation winery will guarantee a greater profit.

Second, from a dynamic point of view, results from this spatial analysis are related to the evolution of reputation and quality. Since locating nearby a high reputation and high price wineries may have price advantage, besides high quality wine producers, low quality wine makers will also be attracted to this area. They produce low class wine but enjoy a higher reputation and price. Moral hazard and adverse selection problems may occur, and thus, the location may no longer be an effective signal for consumers to distinguish good wines from bad ones. In the long run, the collective reputation of the sub-region will be negatively affected. Therefore, possible dynamic equilibrium of wine quality for the sub-region tends to be lower than the initial quality. This can be considered as a by-product of the positive spatial effects among close wineries.

Conclusion

This chapter analyzes spatial effects of winery locations on wine price for both California and Washington State. We first located each winery in our data set accurately on the U.S. map to obtain a visual understanding of winery distribution. Since the precise longitude and latitude are available with GIS software, we can identify "neighbors" for each winery, either by a distance or nearest criterion. We use the "K nearest neighbors" approach as the standard to describe the neighborhood of wineries for both states, since it is more appropriate to the winery distribution.

From Global Moran's I clustering test, wine price and score show significant clustering patterns. This can be the starting point of spatial analyses and confirm our hypothesis about spatial effect among wine producers. Following the statistical tests, formal models are developed for both states. Spatial econometrics methods are applied and the regression results indicate that there exists strong and positive neighborhood effect: if neighbors of a winery had price premium, it is likely that the winery also has price advantage. Therefore, we can conclude that good neighbors have important values. However, the positive spatial effect cannot guarantee maximum profit for a new wine producer who is going to locate in a high price neighborhood because of the tradeoff between higher wine price and higher land cost. Also, this good neighbor value may cause lower dynamic quality equilibrium because it will induce moral hazard and adverse selection problems.

This chapter is the first one to consider spatial effects of wineries in the United States. It provides a new way to apply hedonic analysis on wine price and discovers that location interactions are very important to winery's product price.

References

Anselin, L. (1988a). *Spatial Econometrics: Methods and Models*. Kluwer Academic, Dordrecht.

Anselin, L. (1998a). GIS research infrastructure for spatial analysis of real estate markets. *Journal of Housing Research* 9, 113–33.

Anselin, L. and Can, A. (1995), Spatial Effects in Models of Mortgage Origination. *Paper presented at 91st Annual Meeting of the American Association of Geographers, March 14–18, Chicago.*

Can, A. (1996). Weight matrices and spatial autocorrelation statistics using a topological vector data model. *International Journal of Geographical Information Systems* 10, 009–1017.

Can, A. (1998). GIS and spatial analysis of housing and mortgage markets. *Journal of housing Research* 9, 61–86.

Costanigro, M., Mittelhammer, R.C. and McCluskey, J.J. (2009), Estimating Class-specific Parametric Models under Class Uncertainty: Local Polynomial Regression Clustering in a

Hedonic Analysis of Wine Market. *Journal of Applied Econometrics, Early View*

Frizado, J., Smith, B.W., Carroll, M.C. and Reid, N. (2009), Impact of polygon geometry on the identification of economic clusters, *Letters in Spatial and Resource Sciences*, 2, 31 – 44

Garretsen, H. and Peeters,J. (2009), FDI and the Relevance of Spatial Linkages: Do Third-Country Effects Matter for Dutch FDI? *Review of World Economics, July 2009, v. 145, iss. 2, pp. 319-38*

Jaffe, A.B, Trajtenberg, M. and Henderson, R. (1993), Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations, *The Quarterly Journal of Economics, vol. 108, No.3., 577 – 598*

Kaye-Blake, W., O'Connell, A. and Lamb, C. (2007), Potential Market Segments for Genetically Modified Food: Results from Cluster Analysis, *Agribusiness, Vol. 23 (4), 567 – 582*

Noev, N., (2005), Wine Quality and Regional Reputation: Hedonic Analysis of the Bulgarian Wine Market, *Eastern European Economics*, *Volume 43, Number 6 / November-December 2005, 5 – 30*

Porter, M. (2000), Location, Competition, and Economic Development: Local Clusters in a Global Economy. *Economic Development Quarterly, Vol.14 No.1,* 15-34.

Steiner, B., (2004), French Wines on the Decline? Econometric Evidence from Britain, *Journal of Agricultural Economics, Volume 55, Number 2, July 2004 , pp. 267-288(22)*

Stiler, J.F. (2007), *The House of Mondavi: The Rise and Fall of an American Wine Dynasty.* Penguin, New York, NY.

Tobler, W. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography* 46: 234–40.

Wallsten, S.J. (2001), An empirical test of geographic knowledge spillovers using geographic information systems and firm-level data. *Regional Science and Urban Economics 31, 571 – 599*

Wu, Y., and Hendrick, R. (2009). Horizontal and Vertical Tax Competition in Florida Local Governments. *Public Finance Review, 37,* 289

Table 4.1 Descriptive statistics of the non-binary variables for Washington and Calfornia

Descriptive Statistics

State		Price	Score	Case	Age
Washington (N = 79)	Mean	25.18	86.53	3052.28	2.81
	Min	10.65	78.00	110.00	2.00
	25 quartile	17.86	85.00	296.50	2.50
	Median	23.73	86.67	793.75	2.90
	75 quartile	29.75	88.39	1706.97	3.05
	Max	59.23	92.35	86321.46	4.17
	Std.	10.26	2.88	10153.72	0.52
California (N = 876)	Mean	34.88	85.40	4498.28	2.83
	Min	5.85	70.00	50.00	1.00
	25 quartile	18.00	83.42	450.00	2.43
	Median	25.58	85.91	975.30	2.93
	75 quartile	38.00	87.62	2764.06	3.09
	Max	1267.78	96.00	328333.33	5.50
	Std.	57.06	3.65	16438.23	0.59

* CPI adjusted to 2000

Table 4.2 Brief Descriptions and Abbreviations of Variables

Variables	Short Description	Binary/Non-binary
Score	Rating Score from Wine Spectator	Non-binary
Case	Number of Cases Produced	Non-binary
Age	Years of Aging Before Commercialization	Non-binary
Napa		
BayCentral		
Sonoma		
SouthCoast	Regions of Production in California	Binary
Carneros		
SierraFoothills		
Mendocino		
Columbia Valley		
Yakima Valley	Regions of Production in Washington	Binary
Walla Walla Valley		
Puget		

Table 4.3 Moran's I Tests for Washington State

Models	Variables	I	Sd (I)	Z	P-value
1 nearest neighbor	Price	0.582	0.14	4.239	0.000
	Score	0.209	0.139	1.593	0.056
2 nearest neighbors	Price	0.524	0.099	5.43	0.000
	Score	0.236	0.098	2.538	0.006
3 nearest neighbors	Price	0.526	0.082	6.603	0.000
	Score	0.287	0.081	3.71	0.000
4 nearest neighbors	Price	0.502	0.07	7.332	0.000
	Score	0.235	0.069	3.572	0.000
5 nearest neighbors	Price	0.484	0.062	8.007	0.000
	Score	0.275	0.062	4.677	0.000

Table 4.4 Moran's I Tests for California

Models	Variables	I	Sd (I)	Z	P-value
1 nearest neighbor	Price	0.454	0.042	10.737	0.000
	Score	0.31	0.042	7.347	0.000
5 nearest neighbors	Price	0.395	0.02	20.305	0.000
	Score	0.284	0.02	14.635	0.000
10 nearest neighbors	Price	0.385	0.014	27.824	0.000
	Score	0.272	0.014	19.65	0.000
20 nearest neighbors	Price	0.377	0.01	38.479	0.000
	Score	0.254	0.01	26.03	0.000
30 nearest neighbors	Price	0.363	0.008	45.611	0.000
	Score	0.24	0.008	30.208	0.000
35 nearest neighbors	Price	0.362	0.007	49.345	0.000
	Score	0.24	0.007	32.72	0.000
50 nearest neighbors	Price	0.342	0.006	56.096	0.000
	Score	0.225	0.006	37.073	0.000
60 nearest neighbors	Price	0.334	0.006	60.596	0.000
	Score	0.221	0.006	40.092	0.000

Table 4.5 Spatial Regression results for Washington State

Variables	Spatial Models		
	1 nearest neighbor	2 nearest neighbor	**3 nearest neighbor**
Intercept	-3.1014	-3.1773	**-3.3642**
	(0.001)	(0.001)	**(0.000)**
Score	0.0625	0.0585	**0.0591**
	(0.000)	(0.000)	**(0.000)**
case	-5.45E-06	-5.15E-06	**-5.66E-06**
	(0.056)	(0.065)	**(0.038)**
Age	0.1482	0.1591	**0.1538**
	(0.008)	(0.004)	**(0.004)**
Columbia Valley	-0.2406	-0.2217	**-0.2295**
	(0.023)	(0.032)	**(0.023)**
Yakima Valley	-0.1219	-0.1109	**-0.1193**
	(0.221)	(0.255)	**(0.212)**
Walla Walla Valley	0.1206	0.1043	**0.0564**
	(0.308)	(0.362)	**(0.629)**
Puget	-0.0007	-0.0183	**-0.0359**
	(0.994)	(0.846)	**(0.701)**
Rho	0.1572	0.2770	**0.3314**
	(0.085)	(0.013)	**(0.003)**
Wald test	2.9720	6.1290	**8.6570**
	(0.085)	(0.013)	**(0.003)**
LR test	2.9180	5.8330	**8.1190**
	(0.088)	(0.016)	**(0.004)**
LM test	1.9820	5.0480	**8.6620**
	(0.159)	(0.025)	**(0.003)**
AIC	20.8122	17.8973	**15.6105**

*P-values are in parenthesis

Table 4.6 Spatial Regression results for Washington State (continue)

Variables	4 nearest neighbor	5 nearest neighbor	No Spatial
Intercept	-3.4679	-3.6567	-3.0755
	(0.000)	(0.000)	(0.004)
Score	0.0603	0.0602	0.0676
	(0.000)	(0.000)	(0.000)
case	-5.49E-06	-5.09E-06	-5.85E-06
	(0.047)	(0.064)	(0.059)
Age	0.1482	0.1540	0.1561
	(0.006)	(0.004)	(0.011)
Columbia Valley	-0.2383	-0.2288	-0.2777
	(0.019)	(0.024)	(0.015)
Yakima Valley	-0.1254	-0.1208	-0.1351
	(0.194)	(0.208)	(0.209)
Walla Walla Valley	0.0373	0.0159	0.1840
	(0.760)	(0.897)	(0.132)
Puget	-0.0481	-0.0585	0.0108
	(0.615)	(0.540)	(0.916)
Rho	0.3395	0.3989	N/A
	(0.007)	(0.004)	
Wald test	7.2370	8.4290	N/A
	(0.007)	(0.004)	
LR test	6.8640	7.9440	N/A
	(0.009)	(0.005)	
LM test	7.5470	8.5740	N/A
	(0.006)	(0.003)	
AIC	16.8665	15.7856	19.7300

*P-values are in parenthesis

Table 4.7 Spatial Regression results for California

Variables	Spatial Models			
	1 nearest neighbor	5 nearest neighbors	10 nearest neighbors	20 nearest neighbors
Intercept	1.2966	1.2008	1.1998	1.1602
	(0.000)	(0.000)	(0.000)	(0.000)
Score	-0.0097	-0.0093	-0.0094	-0.0093
	(0.000)	(0.000)	(0.000)	(0.000)
case	5.13E-07	5.12E-07	5.01E-07	5.08E-07
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.0153	-0.0149	-0.0149	-0.0147
	(0.000)	(0.000)	(0.000)	(0.000)
BayCentral	-0.0299	-0.0302	-0.0317	-0.0341
	(0.000)	(0.000)	(0.000)	(0.000)
Carneros	-0.0534	-0.0525	-0.0526	-0.0510
	(0.000)	(0.000)	(0.000)	(0.000)
Mendocino	-0.0162	-0.0166	-0.0167	-0.0178
	(0.0540)	(0.0460)	(0.045)	(0.031)
Napa	-0.0443	-0.0384	-0.0372	-0.0345
	(0.000)	(0.000)	(0.000)	(0.000)
SierraFoothills	-0.0068	-0.0081	-0.0089	-0.0094
	(0.3540)	(0.2650)	(0.219)	(0.195)
Sonoma	-0.0244	-0.0227	-0.0228	-0.0220
	(0.000)	(0.000)	(0.000)	(0.000)
SouthCoast	-0.0171	-0.0171	-0.0167	-0.0175
	(0.0010)	(0.0010)	(0.000)	(0.000)
Rho	0.1028	0.2366	0.2494	0.3110
	(0.000)	(0.000)	(0.000)	(0.000)
Wald test	19.4190	41.2870	39.4490	51.9940
	(0.000)	(0.000)	(0.000)	(0.000)
LR test	19.1960	40.3260	38.5550	50.4670
	(0.000)	(0.000)	(0.000)	(0.000)
LM test	13.9310	37.8090	44.4240	62.9270
	(0.000)	(0.000)	(0.000)	(0.000)
AIC	-3139.313	-3160.443	-3158.673	-3170.584

*P-values are in parenthesis

Table 4.8 Spatial Regression results for California (continue)

Variables	Spatial Models				
Variables	30 nearest neighbors	**35 nearest neighbors**	50 nearest neighbors	60 nearest neighbors	No Spatial
Intercept	1.1493	**1.1469**	1.14565	1.1461	1.3805
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.000)
Score	-0.0093	**-0.0093**	-0.0093	-0.0094	-0.0101
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.000)
case	5.09E-07	**5.07E-07**	5.08E-07	5.08E-07	5.40E-07
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.000)
Age	-0.0146	**-0.0145**	-0.0145	-0.0146	-0.0158
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.000)
BayCentral	-0.0341	**-0.0346**	-0.0360	-0.0360	-0.0321
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.000)
Carneros	-0.0513	**-0.0502**	-0.0504	-0.0502	-0.0589
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.064)
Mendocino	-0.0181	**-0.0174**	-0.0161	-0.0159	-0.0159
	(0.028)	**(0.034)**	(0.051)	(0.053)	(0.000)
Napa	-0.0341	**-0.0338**	-0.0335	-0.0330	-0.0503
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.352)
SierraFoothills	-0.0106	**-0.0119**	-0.0136	-0.0137	-0.0070
	(0.145)	**(0.099)**	(0.062)	(0.061)	(0.000)
Sonoma	-0.0218	**-0.0216**	-0.0217	-0.0214	-0.0269
	(0.000)	**(0.000)**	(0.000)	(0.000)	(0.001)
SouthCoast	-0.0183	**-0.0178**	-0.0180	-0.0178	-0.0181
	(0.000)	**(0.000)**	(0.001)	(0.001)	(0.000)
Rho	0.3345	**0.3406**	0.3585	0.3649	N/A
	(0.000)	**(0.000)**	(0.000)	(0.000)	
Wald test	54.1350	**55.2010**	54.3890	53.8100	N/A
	(0.000)	**(0.000)**	(0.000)	(0.000)	
LR test	52.4740	**53.4780**	52.7230	52.1660	N/A
	(0.000)	**(0.000)**	(0.000)	(0.000)	
LM test	69.3190	**71.5670**	71.3490	71.8850	N/A
	(0.000)	**(0.000)**	(0.000)	(0.000)	
AIC	-3172.591	**-3173.595**	-3172.84	-3172.283	-3124.117

*P-values are in parenthesis

Figure 0.1 Winery Distribution for Washington State

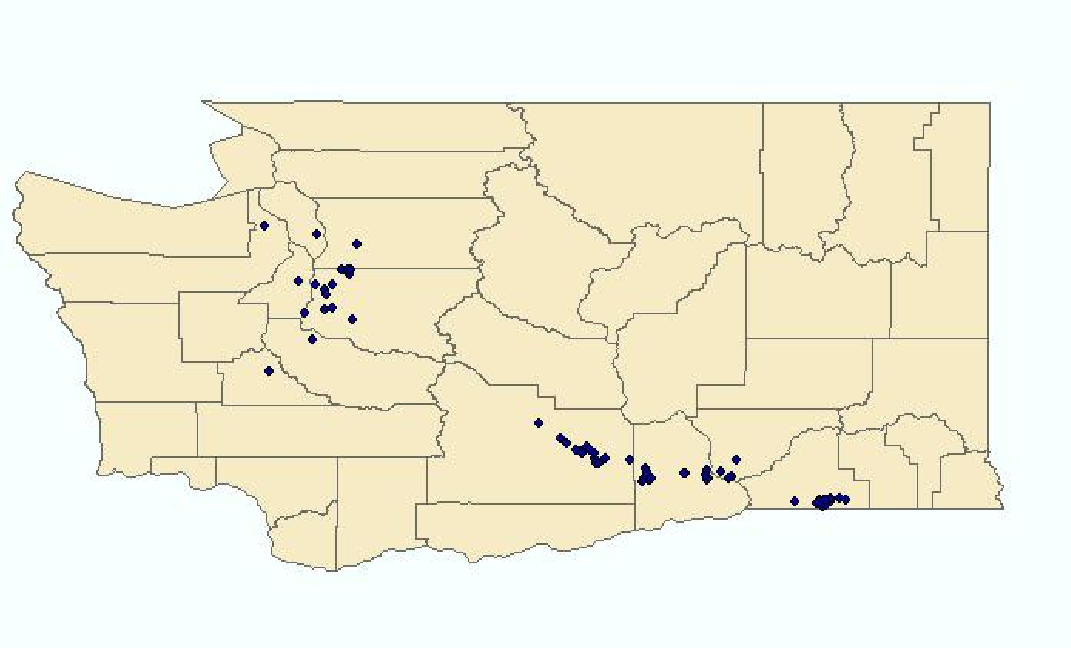

Figure 0.2 Winery Distribution for California State

CHAPTER FIVE

CONCLUSIONS

This dissertation analyzed how quality factors affect wine price and consumer's purchase behaviors from three different but related aspects: wine's sensory properties, organic classifications for wine and spatial interactions among wineries.

The findings indicate all these factors have significant effects on wine price or consumer's purchase behaviors, no matter positive or negative. From these results, one can get deeper understanding about economics natures of wine's characteristics, make more predictive decisions and adjust behaviors to affect outcomes.

However, all studies conducted in this dissertation are focused on the market side of wine. Issues related to the production of wine are generally not included and not discussed, such as the cost of adding a new characteristic to existing wine, and risk of taking a new action. Therefore, the results shown in this dissertation are significant but with limits. In order to fully guide the wine industry which goal is to maximize profit, a study about wine cost should also be considered.