The Value of Good Neighbors: A Spatial Analysis of the California and Washington State Wine Industries

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ABSTRACT. *The fact that wineries tend to cluster 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 from California and Washington State with GIS coordinates are utilized to examine the spatial relationships among neighboring wineries. Spatial effects are assessed by performing clustering tests based on wine prices and tasting scores. A spatial-lag model is then estimated to test whether there are positive effects from neighbors in a hedonic price estimation. The results indicate that strong and positive neighbor effects are present.* (JEL Q11, R32)

I. 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)

Microregions for wine have their own unique combination of climate and soils, called *terroir,* that create distinct flavor characteristics. From these grapes, a skilled craftsman, informed by local knowledge built over many generations, coaxes flavors into a recognizable combination. Wine should have the physical and cultural characteristics of a specific location embodied in it. Is this a romanticized view of wine production? Probably, but even so, many researchers have found that variables indicating the locations of wineries significantly influence their market prices. Wine is a highly differentiated product, and consumers are uncertain about quality and characteristics. Consequently, they use location information combined with expert opinion when considering price and quality trade-offs. Brand development also depends on wine tourism in which consumers develop preferences for wines produced by the wineries they have visited.

All of these factors suggest that there are many reasons for wineries to be clustered together spatially. Even in an area with ideal growing conditions, an isolated winery will lack an appellation designation that consumers recognize. An isolated winery might also attract fewer potential visitors, who would prefer to tour a number of wineries with as little travel as possible in a region with a well-developed wine tourism industry. Producers may also benefit from scale economies and knowledge spillovers.

While these agglomerating forces pull wineries together over time, other forces may build that push them apart. Pests and/or diseases are a possible negative spatial externality. In some cases, a plant pathogen may spread (aerially or via insect vectors) from nearby farms. If a winery is isolated, it would be less likely to get the disease. The benefits of clustering are likely to be capitalized into land values. At what point do higher land prices cause market entrants to choose a location with a cheaper land price even though that location would initially put them at a disadvantage in the market? The advantages to locating near renowned wineries in a recognized appellation could also be dissipated if wine producers free ride on the labeling premium associated with the collective reputation by producing wine more cheaply, and of lower quality, in order to increase profits (see Winfree and McCluskey [2005] for a theoretical analysis of collective reputation). This

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The authors are, respectively, postdoctoral researcher; professor; and assistant research professor, School of Economic Sciences, Washington State University, Pullman.

inflicts a negative externality on neighboring wine producers. Over time, these incentives may erode the premium that wines from a well-known appellation can command.

There has been a marked increase in interest about the role that spatial effects play in economics, and it has infiltrated the mainstream literature while being nurtured in the subfields of the new economic geography (Krugman 1991; Fujita, Krugman, Venables 1997), urban economics, regional science, and spatial econometrics (not a mutually exclusive list). The incorporation of the spatial dimension into economic models is often compared to time-series methods, but space is inherently more complex because it is multidimensional, and identifying a relevant spatial index can be difficult. Wine production is interesting because of all the potential avenues for spatial effects to arise. Growing wine grapes is an agricultural process, but there is value added from making grapes into wine. Knowledge spillovers have been shown to influence production practices in agriculture (Conley and Udry 2009). Shared labor resources can also lower production costs, which are often hypothesized as major drivers of firm clustering in a number of industries. Lower costs from shared resources, in large part, explains the existence of cities (Gottlieb and Glaeser 2009). Ceteris paribus, an isolated winery should find it more costly to attract workers. Consumers use both appellation labels and wine touring to learn about and choose between wines. The relative effect of these attractive forces versus the repulsive effect of higher land prices will determine how wine regions develop over time in terms of spatial concentration, quality, and price. Spatial effects appear to be a critical part of the economics of wine production, so they are an important, yet largely unexplored, area of research.

Spatial econometric models provide a general approach for handling spatial autocorrelation in cross-sectional and panel data. Minimally, this approach provides a framework for addressing estimation problems that may arise from ignoring a spatial data generating process when one is present. For example, if each winery's production decisions depend on decisions made by other wineries, then observations of the dependent variable are no longer independent. As previously discussed, there are potentially many reasons why wine producers may interact in a spatially dependent manner that could lead to spatial clustering. The standard approach for dealing with this type of dependency is to include a spatial lag of the dependent variable as an explanatory variable.

In this article, we bring together the spatial hedonic literature, which has been used primarily to analyze land use and land value questions, with the literature on hedonic modeling of consumer goods. Both standard forms of spatial econometric models, the spatial lag and the spatial error models, have been used in spatial hedonic studies. Wine is an interesting application of this class of models because the assumption that decisions are dependent in a single cross section is much less problematic than for a market with time frictions, such as the housing market (Anselin and Lozano-Gracia 2008). Wine prices respond within season to the pricing of other wines. Supply may also be responsive, as inventory of aging wines can be released.

Spatial error models used to account for spatial heterogeneity can assume it takes either a discrete or a continuous form. In spatial hedonic models, this typically involves designating a finite set of mutually exclusive neighborhoods. The consideration of continuously variable spatial heterogeneity has led to the development of approaches, such as the geographically weighted regression. Fotheringham et al. (2002) offer a general discussion, and Cho, Bowker, and Park (2006) and Gelfand et al. (2003) present spatial hedonic examples. Hedonic spatial autoregressive models have been widely used for valuing environmental resources using parcel-level data (e.g., Brasington 2004; Hui et al. 2007), particularly for air quality (Kim, Phipps, and Anselin 2003; Beron et al. 2004). These studies routinely find significant differences in estimates of implicit prices compared to nonspatial models (Anselin and Lozano-Gracia 2008). While maximum likelihood remains the most popular approach for estimation, alternative approaches such as general method of moments estimators are also used (e.g., Bell and Bockstael 2000).

A number of studies have used hedonic models to estimate the implicit prices for various characteristics of wine (e.g., Oczkowski 1994, 2001; Landon and Smith 1997, 1998). Nerlove (1995) uses a modified hedonic model regressing quantity on price and quality attributes for a sample of Swedish wine consumers and finds results to vary significantly from the traditional specification. Unwin (1999) provides a critique of wine hedonic models. While Unwin (1999) believes it best to abandon hedonic approaches, Thrane (2004) argues that with some modifications, they are still useful. Combris, Lecocq, and Visser (1997) use an extensive list of objective sensory characteristics and determine that these primarily drive wine price, rather than labeling characteristics. Using market prices and product attributes, Costanigro, McCluskey, and Mittelhammer (2009) identify market segments for Washington State and California wines with a new econometric procedure, local polynomial regression clustering, applied to a hedonic model. Kaye-Blake, O'Connell, and Lamb (2007) utilize cluster analysis on potential market segments for genetically modified food, based on survey responses. To our knowledge, no previous studies have focused on the economics of geographic clustering of wineries.

In the current study, we exploit a detailed winery-level geographic information system (GIS) data set. Using wineries' mailing addresses collected from all California and Washington State wines listed in *Wine Spectator* magazine, we created a GIS data set. This is a significant improvement over regional or appellation information used in previous studies. For the analysis, we first conduct statistical tests to examine whether geographic winery clusters exist based on prices and expert rating scores. A spatial lag model is then estimated to test the hypothesis that there are positive effects from neighbors when analyzing hedonic price equations for wine.

Spatial analyses of California and Washington wine industries can improve our understanding of the economic relationships among prices, other product attributes, and reputations that are influenced by location. We depart from previous studies that either ignore the spatial autocorrelations among wineries or incorporate them into the error structure of the regression model. Since spatial effects are likely, if one ignores the spatial nature of the data, it may lead to biased or inefficient estimates and misleading inference (Anselin 1988).

II. DATA

The data set consists of winery-level data for red wines from Washington and California. For each observation, information about price, rating score, case, years of aging, vintage, and production region is collected from *Wine Spectator* magazine (online version). Since the observed unit in this study is the individual winery, the above variables of price, score, case, and age are averaged across wines for each winery in our data set. Consequently, there is a maximum of one observation per winery. Indicator variables are used to denote the winery's production area, representing collective reputations.

The macro wine regions for California (Figure 1) include Napa, Sonoma, Mendocino, Bay Area, South Coast, Carneros, Sierra Foothills, and other California. In Washington (Figure 2), they are Columbia Valley, Yakima Valley, Walla Walla, Puget Sound, and other Washington. There are 137 observations for wineries in Washington and 1,195 observations for wineries in California that have vintages listed in *Wine Spectator* during the period of study. However, owing to the instances of missing address information (e.g., some wineries provide only a post office box or list only a city), 79 wineries from Washington and 876 wineries from California are analyzed in the study. Table 1 reports the descriptive summary of nonbinary variables in our data set, and Table 2 provides brief descriptions and abbreviations of all variables used in the empirical analyses.

In order to describe the spatial property of each winery, we incorporate GIS data into our study. We obtained a name and address for each winery. The address information allows us to recover the latitude and longitude coordinates of each winery's postal address, which is where we assume the wine production takes place. This may or may not coincide with the grape production, as some wineries purchase

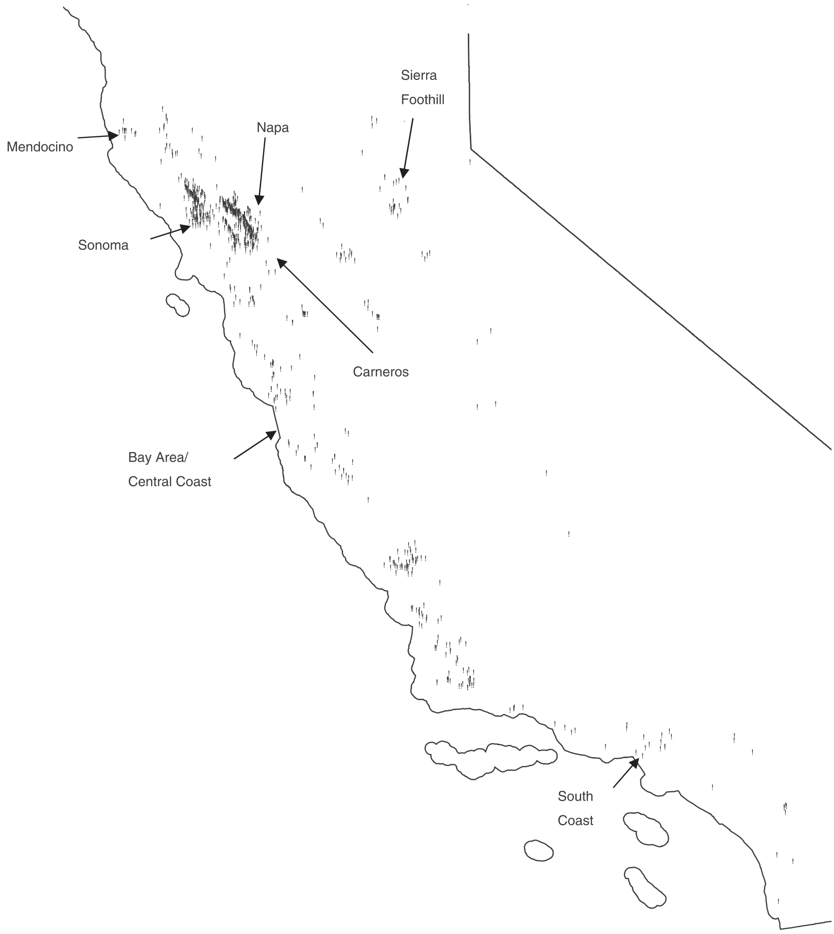

FIGURE 1
California Macro Wine Regions and Locations of Wineries

grapes from other growers. We acknowledge that blending of grapes from different regions may dilute the spatial effect. Following geocoding, we can obtain an understanding of almost any 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 California and Washington. Figures 1 and 2 depict the distributions of winery locations for California and Washington, respectively. Regarding the spatial information of our data set, two things need to be mentioned. First, we only include wineries whose wines are listed in *Wine Spectator*, which means that there is a lower bound for quality or product class. No boxed wines or "jug wines" are included. Second, among all the wineries, in Washington, 10% of them are "estate" wineries, and 5% are "estate" wineries in California. These wineries use only their own grapes to produce wine instead of buying any grapes from external growers.

III. METHODS AND MODEL

The price of a bottle of wine is generally considered to be a function of expert subjec-

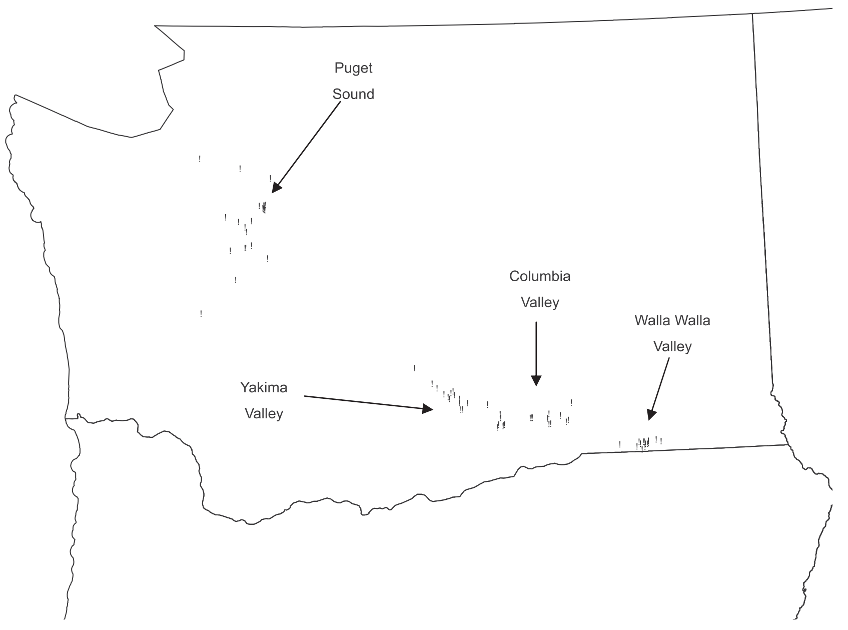

FIGURE 2
Washington Macro Wine Regions and Locations of Wineries

TABLE 1
Descriptive Statistics for the Nonbinary Variables

	Price[a]	Score	Cases[b]	Age
Washington ($N = 79$				
Mean	25.18	86.53	3.05	2.81
Min	10.65	78.00	0.11	2.00
25th percentile	17.86	85.00	0.30	2.50
Median	23.73	86.67	0.79	2.90
75th percentile	29.75	88.39	1.71	3.05
Max	59.23	92.35	86.32	4.17
Std. Dev.	10.26	2.88	10.15	0.52
California ($N = 876$)				
Mean	34.88	85.40	4.50	2.83
Min	5.85	70.00	0.05	1.00
25th percentile	18.00	83.42	0.45	2.43
Median	25.58	85.91	0.98	2.93
75th percentile	38.00	87.62	2.76	3.09
Max	1,267.78	96.00	328.33	5.50
Std. Dev.	57.06	3.65	16.44	0.59

[a] In dollars, adjusted by the Consumer Price Index to 2000 prices.
[b] In thousands.

TABLE 2
Number of Observations

Macroregions	Observations
California	
Napa	265
Bay Area	37
Sonoma	237
South Coast	155
Carneros	13
Sierra Foothills	43
Mendocino	30
Washington	
Columbia Valley	14
Yakima Valley	17
Walla Walla Valley	15
Puget Sound	23

tive measures of quality in the form of a score, quantity supplied, age, and the wine growing region. Many studies have analyzed tastes attributes, but consumers typically buy wine without having tasted it. In fact, this is why wine scores and appellations are so important in determining wine prices. Consumers look for them as they form expectations about the attributes and quality of a wine. In addition, *terroir* and proximity to other wineries are spatially dependent factors that are likely to affect the price of a wine. Omitting the variables that represent growing conditions may result in potentially inefficient and inconsistent standard errors. The effect of growing conditions on wine quality has been considered in a number of different ways in previous studies. Ashenfelter, Ashmore, and Lalonde's (1995) prediction model of quality based on weather data is a prominent example. The well-known spatial error model could be used to correct for spatial autocorrelation in the error structure.

Another aspect to spatial dependence, which has received less attention in analyzing the wine industry, is the interaction that occurs between wineries depending on their proximity to each other. In contrast to correcting for spatial dependency in the errors, this sort of interaction is the spatial process that occurs in situations in which economic agents make decisions that affect other agents heterogeneously across space. Carried out over space and time, actions and reactions will transpire until no firm has an incentive to change, which constitutes a spatial equilibrium. The Mondavi quote provided at the beginning of the article offers an example of the many potential ways that negative and positive externalities can result in positive correlation in wine prices across space. A winery located near other highly regarded wineries is likely to gain greater recognition and have an easier time marketing its wine. Alternatively, an isolated winery may struggle to gain recognition, and if the quality of wine produced by a neighbor is poor, then perceptions of the quality of the area will suffer.

In order to capture these interactions, we include within the hedonic price model a spatial lag term that includes a scalar spatial lag parameter ρ multiplied by a spatial weight matrix $\mathbf{W}$, and a vector of spatial lags of the dependent variable $\mathbf{P}^*$ where the asterisk denotes that price is transformed as explained below.

$$\mathbf{P}^* = \rho\mathbf{W}\mathbf{P}^* + \mathbf{X}\boldsymbol{\beta} + \varepsilon. \qquad [1]$$

$\mathbf{X}$ is a vector of explanatory variables that includes score, age, cases, and region, $\boldsymbol{\beta}$ is a vector of coefficients to be estimated.

Score is the rating score from *Wine Spectator* magazine. *Case* is the number of cases produced by the winery, scaled by 1,000. *Age* represents years of aging before commercialization. All of these variables are average values for the particular winery across the observation period. *Region* indicates the region of production. For Washington there are four regions: Columbia Valley, Yakima Valley, Walla Walla Valley, and Puget Sound. For California, there are seven regions: Napa Valley, Bay Area, Sonoma, South Coast, Carneros, Sierra Foothills, and Mendocino. The excluded regions are other Washington or other California, so that the region parameters indicate the difference between wines from the specific macroregion and the generic Washington or California wines.

Hedonic price theory does not give the researcher guidance in choosing a functional form (see Costanigro and McCluskey 2011 for a discussion). Consequently, we use a Box-Cox transformation to specify the form of the dependent variable price (P). Based on these estimations, for Washington, we specify $P^* = \ln(P)$ as the final dependent variable in the regression. For California, the best transformation is $P^* = P^{-0.25}$. The specification of the spatial weight matrix is a critical part of specifying this class of models. In previous studies, Frizado et al. (2009) emphasize the sensitivity of spatial weights matrix selection to the cluster identification results with local Moran's and Getis-Ord Gi statistics. They conclude that the selection of spatial weighting methodology should depend on the study's purpose, the distribution of the variable being studied, and the industry being studied. Further, Anselin (1999) points out that the elements of the weighting matrix are nonstochastic 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 the literature, such as the inverse distance or inverse distance squared (Anselin 1980), the structure of a social network (Doreian 1980), the economic distance (Case, Rosen, and Hines 1993), and the K nearest neighbors (Pinkse and Slade 1998).

The specification of spatial weights is not arbitrary. The range of dependence allowed by the structure must be constrained. Therefore, the key question in every spatial econometric analysis is how to define the range of the neighborhood. Intuitively, if the firms all belong to one cluster, then distance decay will be a reasonable choice of spatial weights, because that specification treats all units as neighbors. However, when firms are dis-

TABLE 3
Moran's I Tests for Washington

Models	Variables	I	SD (I)	Z	p-Value
1 nearest neighbor	Price	0.582	0.140	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	0.070	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

tributed as several spatial "hot spots," only considering a distance weight would be inappropriate. Further, in order to avoid confusing the exogeneity of weights, deriving weights geographically is more appropriate.

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

Clustering Test (Global Moran's *I*)

Before proceeding to the spatial econometric analysis, we identify the extent of spatial correlation in wine prices unconditional on any other variables. In the current study, we seek to understand the spatial relationships among wineries within a state. Global Moran's I statistic can be used to evaluate whether the spatial distribution pattern is clustered, dispersed, or random. Global Moran' I statistic is defined as

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j \mathbf{W}_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_i (X_i - \bar{X})^2}, \qquad [2]$$

where N is the number of spatial units indexed by i and j, representing the value of the variable of interest for wineries i and j, and $\mathbf{W}_{ij}$ is a matrix of spatial weights, which are defined by K nearest neighbors criteria. X represents the variables of interest, and $\bar{X}$ is the mean of X. For wineries, we utilize prices and scores. The values of global Moran's I statistic can range from -1 (indicating perfect dispersion) to $+1$ (perfect clustering). Inference from the global Moran's I statistic 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 level for significance is set at 95% level of confidence, then a Z-score must be less than -1.96 or greater than 1.96 to be statistically significant.

The results from global Moran's I tests for price and score for Washington and California are presented in Tables 3 and 4. The K nearest neighbors' spatial weight matrix was estimated for K from 1 to 5 for Washington and for 1 to 65 for California. In all the estimations, both price and score exhibit positive clustering distributions at the global level. Further, comparing the Moran's I values, price clustering is stronger than score clustering.

IV. RESULTS AND DISCUSSION

The AIC values are used as the criteria for model selection. For each state, we estimated models for K from 1 to 5 for Washington and from 1 to 65 for California, where K is the number of nearest neighbors, and calculated AIC statistics for each model. Table 5 presents the AIC statistics for different values of K. For Washington, the three nearest neighbors ($K = 3$) spatial structure performs best

TABLE 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	0.310	0.042	7.347	0.000
5 nearest neighbors	Price	0.395	0.020	20.305	0.000
	Score	0.284	0.020	14.635	0.000
10 nearest neighbors	Price	0.385	0.014	27.824	0.000
	Score	0.272	0.014	19.650	0.000
20 nearest neighbors	Price	0.377	0.010	38.479	0.000
	Score	0.254	0.010	26.030	0.000
30 nearest neighbors	Price	0.363	0.008	45.611	0.000
	Score	0.240	0.008	30.208	0.000
35 nearest neighbors	Price	0.362	0.007	49.345	0.000
	Score	0.240	0.007	32.720	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 5
AIC Values for *K* Nearest Neighbors

K Nearest Neighbors	Washington	*K* Nearest Neighbors	California
0	19.730	0	− 3,124.117
1	20.812	1	− 3,139.313
2	17.897	5	− 3,160.443
3	15.610	10	− 3,158.673
4	16.867	20	− 3,170.584
5	15.786	30	− 3,172.591
		35	− 3,173.595
		40	− 3,172.152
		50	− 3,172.840
		60	− 3,172.283

Note: AIC, Akaike's information criterion.

with the smallest AIC value of 15.611, and consequently, we present the results of that model in Table 6. Three wineries represent about 4% of the total wineries that are listed for Washington in the *Wine Spectator* ratings data base. For California, we find that the AIC value reaches its minimum when $K = 35$, which is also about 4% of the total wineries listed in California. We expected the number of wineries considered as neighbors in California might be greater than in Washington because California has more wineries and the distance between wineries is generally smaller. Consequently, the spatial estimation results for California with $K = 35$ are reported in Table 6.

In Table 6, we also provide estimation results from the hedonic model without a spatial lag term. Further, statistics from Wald, likelihood ratio (LR) and Lagrange multiplier (LM) tests are presented to evaluate the hypothesis that there are no significant spatial relationships among wineries. From the results for both states, according to the Wald, LR, and LM tests, ρ is significantly different from zero and has a positive sign. Since ρ is the parameter describing the spatial correlation, this result indicates that the *K* nearest neighbors have a significant and positive effect on a winery's own product price. Therefore, we conclude that high-performing neighbors have significant and positive effects on winery's product price for both states' wineries. This finding is consistent with positive spillover theory, and it can be important to potential investors who are interested in developing new wineries.

We first discuss the hedonic regression estimates for Washington. The results are consistent with economic theory and previous studies. As expected, the ratings scores have a significant and positive effect on price. Also, as expected, from the law of demand, the number of cases has a significantly negative impact on price. The years of aging affects price positively. All of the region indicator variables except Columbia Valley are statistically insignificant, and Columbia Valley

TABLE 6
Spatial Regression Results

Variables	Washington		California	
	Spatial Model $K=3$	No Spatial	Spatial Model $K=35$	No Spatial
Intercept	− 3.3642 (0.000)	− 3.0755 (0.004)	1.1469 (0.000)	1.3805 (0.000)
ρ	0.3314 (0.003)	—	0.3406 (0.000)	—
Score	0.0591 (0.000)	0.0676 (0.000)	− 0.0093 (0.000)	− 0.0101 (0.000)
Cases	− 0.0057 (0.038)	− 0.0058 (0.059)	0.0005 (0.000)	0.0005 (0.000)
Age	0.1538 (0.004)	0.1561 (0.011)	− 0.0145 (0.000)	− 0.0158 (0.000)
Columbia Valley	− 0.2295 (0.023)	− 0.2777 (0.015)	—	—
Yakima Valley	− 0.1193 (0.212)	− 0.1351 (0.209)	—	—
Walla Walla	0.0564 (0.629)	0.1840 (0.132)	—	—
Puget	− 0.0359 (0.615)	0.0108 (0.540)	—	—
Bay/Central	—	—	− 0.0346 (0.000)	− 0.0321 (0.000)
Carneros	—	—	− 0.0502 (0.000)	− 0.0589 (0.064)
Mendocino	—	—	− 0.0174 (0.034)	− 0.0159 (0.000)
Napa	—	—	− 0.0338 (0.000)	− 0.0503 (0.352)
Sierra Foothills	—	—	− 0.0119 (0.099)	− 0.0070 (0.000)
Sonoma	—	—	− 0.0216 (0.000)	− 0.0269 (0.001)
South Coast	—	—	− 0.0178 (0.000)	− 0.0181 (0.000)
Wald test	8.6570 (0.003)	—	55.2010 (0.000)	—
LR test	8.1190 (0.004)	—	53.4780 (0.000)	—
LM test	8.6620 (0.003)	—	71.5670 (0.000)	—

Note: p-Values are in parentheses. LM, Lagrange multiplier; LR, likelihood ratio.

receives a discount compared to other Washington wines. Therefore, for most regions, regional differences are not currently valued by the market within Washington. The insignificant effect of the Washington regions may be a reason why consumers usually do not refer to micro wine production regions for Washington, as they do with Californian wine appellations.

For California, since the dependent variable is the -0.25 power transformation of price, a negative sign for the parameter estimate indicates a positive marginal effect on price. The effect of rating scores and aging are positive and significant, while the number of cases produced affects price negatively. All the region indicators, except for the Sierra Foothills, have a significant price premium compared to generic California red wines. This finding suggests that in contrast to Washington, region differences are used by consumers in their assessments of California wines.

To summarize, estimating a spatial autoregression model has the benefit of avoiding omitted variables bias while also estimating the magnitude and statistical significance of spatial dependence between wineries. As shown in Table 6, coefficient estimates between the spatial and nonspatial models are nearly identical for case and age, while there is a larger disparity for score and many of the regional indicator variables. It is interesting to consider the change in coefficient estimates for Napa and Sonoma to develop intuition. The nonspatial model likely overestimates the benefit of having a winery in Napa or Sonoma, because the effect is confounded with the benefit of being proximate to wineries that demand higher prices for their wines. Informed only by the results of the nonspatial model, someone deciding where to locate a winery would overestimate the benefit of a location in an appellation such as Napa or Sonoma.

The spatial model shows that while there is a benefit to being in Napa or Sonoma, there is an additional benefit to being a neighbor of a winery that commands higher prices. We should also note the caveat that this article does not consider the cost side, so we cannot say it is better to locate in one spot over another, given that many benefits may be capitalized into land values. Even so, if an investor relied on the nonspatial model to decide where to locate, then land prices for properties within Napa or Sonoma that are farther away from high-reputation wineries would likely be overpriced.

V. CONCLUSIONS

This article is the first to analyze a GIS data set to understand the spatial effects of winery locations on wine prices. It provides a new way to apply hedonic analysis on wine price and quantifies that location interactions are important to winery's product price. Our analyses of Washington and California wine prices suggest that clustering exists and positively affects price. From the global Moran's *I* clustering test, we find that both wine prices and expert rating scores show significant clustering patterns. The estimated results of a hedonic spatial lag model provide supporting evidence for the hypothesis that positive neighborhood effects exist.

These findings point to a number of interesting questions for future research. One avenue for future research is to explore the factors by which nearby neighboring wineries affect each other's prices. The price-influencing mechanism could be the similar *terroir* within the clusters and/or may be spillover effects from knowledge and reputation. One could construct a spatial panel data set that would make it possible to eliminate the effect of time-invariant spatial heterogeneity. This would make it possible to eliminate the influence of time-invariant characteristics such as *terroir*.

From a dynamic point of view, results from this spatial analysis are related to the evolution of reputation and quality. Since a location nearby a high-reputation wineries results in higher prices, low-quality wine makers will also be attracted to this area. They have an incentive to free-ride on the collective reputation of the region by producing lower-quality wine but enjoying a higher reputation and price. As a result, this may undermine the location as an effective signal for consumers to distinguish good wines from bad ones. In the long run, the collective reputation of the subregion may be negatively affected (Winfree and McCluskey 2005). Therefore, a possible dynamic equilibrium of wine quality for the subregion tends to be lower than the initial quality. This can be considered as a by-product of the positive spatial effects among neighboring wineries.

Finally, the cost side of locating nearby a high-reputation winery should be analyzed. For an entrepreneur who wants to start a new winery, land prices may be so high that it is not profit-maximizing to choose a location right next to a high-reputation winery. The price of land that is located in close proximity to a high-reputation winery should already include capitalized value for the potential to produce high-priced wines.

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