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Model selection and Akaike Information Criteria: An example from wine ratings and prices

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Abstract

The effect of wine ratings on pricing has been a question for wine consumers for some time. Ultimately, wine preference, and thus how one judges a wine, is a subjective endeavor. Wine professionals have long rated wines and those published ratings have some effect on consumer sales. Previously, wine studies have found that there is a connection between rating and price. This study looks to try to verify that connection through insuring that best fit model development is used. For the first time in wine research, the authors have utilized Akaike Information Criteria (*AIC*) to compare different models and more dynamic hypothesis testing to explore the relationship between ratings and prices of wines. In the end, it was confirmed that there is a link, and the use of *AIC* also helped to not only confirm previous findings, but also to identify a new concern in wine ratings.

Keywords: Wine; Wine rating; Model testing; Akaike Information Criteria

1. Introduction

Doubtlessly, wines have been assessed since we first started to consume them. Whether it be the 1855 Bordeaux classification or the multitude of informal wine ratings performed by internet bloggers, cooking magazines, mail-order retailers, and other sources, these evaluations have impacted how wines have been priced and how consumers have accepted these wines. None, however, have been as dominant or divisive as the ratings of Robert Parker and the Wine Spectator.

In the field of economics, an "experience good" is something that is difficult to detect before the actual consumption of that product (Nelson, 1970). For wine, being and experience good, consumers must rely on quality evaluations by product experts. This is not dissimilar to other products for which Consumer Reports provides quality evaluations, only consumers have to look for ratings by Wine Spectator, the WineAdvocate, the Wine Enthusiast, phone apps, blogs and a multitude of other ways for quality ratings of wine. As found in research by Roberts and Reagans (2007) on critical exposure and price–quality relationships, consumers are concerned about quality and rely on "expert opinion."

There have been many that have worked to assess wine quality and to tie that with a pricing model. The literature explores all manner of methods including wine's quality, status, and so forth. Landon and Smith (1998) suggested that a wine's reputation showed to have a greater influence on price, even more so than its actual quality. The study by Roberts and Reagans (2007) found that ratings do have an actual effect on pricing strategies of producers and that prior ratings influence the pricing decisions of a current release. That said, another study Lockshin (1993) found when a new vintage is released, the wholesale price is determined by the taste and negotiations between the maker and the wholesaler. This was confirmed through discussions with distribution companies, as expert

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tasting and evaluations are part of the negotiation and pricing decisions. And lastly, Roberts and Reagans (2007) also found that practiced wine analysts reach comparable conclusions about quality most of the time.

Other research shows to have used hedonic price modeling to help us to better understand how wine pricing and quality relate. Combris et al. (1997) and Landon and Smith (1998), used sensory methods to try and determine the quality of wines from Bordeaux. This concluded in the development of a pricing system based on these influences. However, they failed to address the simpler problem of whether ratings correlate with price. Researchers have looked at hedonic prices for wine attributes and found that ratings do have an effect on what consumers are willing to pay for a wine (Schamel and Anderson, 2003). For this study, the authors did not want to look at consumer's willingness to pay, as price can vary greatly in the United States by retail or restaurant venue. Also, while acknowledging the importance of hedonic pricing models, the authors felt that previous research has already done a good job of addressing wine as a product category.

In a study on the price/quality connection in Bordeaux wines, Landon and Smith (1998) found a positive association between the ratings of Wine Spectator and the wines' reported price. Similarly, others have found the same connection with one using the Connoisseur's Guide (Benjamin and Podolny, 1999) in a study of wines from California and another the study of wines from Australia and New Zealand using quality ratings from James Halliday and Winestate (Schamel and Anderson, 2003). Another study looked at wide variances in listed prices of the Wine Spectator's ratings of 2001 vintage of California Cabernet Sauvignon but not wholesale pricing. Ultimately, it was found that only a handful of articles address wine in relation to price and ranking by wine critics, and only one has looked at it from the wholesale standpoint. We chose to look at wholesale pricing and a more accurate descriptor of price because restaurants and other hospitality providers typically purchase wines from a wholesale distributor that tends to have exclusive distribution of a wine within a region or state. This is a more accurate and stable price for a wine, as retailer and restaurant mark-up is not stable nor standard.

To sum it up, wine reviewers, such as those from the Wine Spectator magazine, impact choices of consumers and thus wine sales. A previous study by Taylor and Baber (2009) found the wholesale price and vintage of a wine were significant in the predictors of a wine's rating. However, it is not clear that the researchers in that study chose the correct model to arrive at that conclusion. For the current study, the use of Akaike Information Criteria (*AIC*) will help to reinforce or debunk the previous findings.

Null hypothesis testing, in the sense that some value is calculated and then compared against some critical value in a given distribution, is a firmly established statistical practice. In regression analysis, a *t*-value is often the value of interest, and this *t*-value is in turn at least somewhat dependent upon the model or equation estimated. However, quite often, the model itself receives only a cursory thought. Many times, researchers are interested only in the relationship between two variables, while the regression equation or model estimated is merely a means to an end. This can have certain drawbacks. An underfitted model may not adequately capture the true nature of what determines the variable of interest; an over-fitted model may increase variability in the estimated equation or lead to information loss in increased degrees of freedom. Ideally, a model would be able to capture the true relationship between the variables of interest while not losing generality from overfitting the data, or what Burnham and Anderson (2002) call a "parsimonious model". Multimodal inference, in the form of Akaike Information Criteria (*AIC*), is a powerful method that can be used in order to determine which model best fits this description. This paper uses *AIC*, along with traditional null-hypothesis testing, in order to determine the model that best describes the factors that influence the rating for a wine. Specifically, once the best model is determined, the relationship between a wine's price and its rating is explored.

2. Research background

2.1. A brief background on AIC

AIC was first developed by Akaike (1973) as a way to compare different models on a given outcome. For example, if researchers are interested, as in this paper, in what variables influence the rating of a wine and how these variables influence the rating of a wine, one may estimate several different regression models. For example, the price of the wine, the type of grape used, or the region the wine was produced in may all play a role in determining the rating of a wine. Regression equations may be run that include just price, or price and region information, or any other combination of variables. Often, though, the model itself receives little thought and is treated as only a tool to reveal the relationship between the outcome and a specific variable. As discussed above, the selection of the model is important, as under-fitting a model may not capture the true nature of the variability in the outcome variable, while an over-fitted model loses generality. *AIC* is then a way to select the model that best balances these drawbacks. Once a best model is selected, traditional null-hypothesis testing can then be used on the best model to determine the relationship between specific variables and the outcome of interest.

Akaike (1973) showed that this selection of the "best" model is determined by an *AIC* score:

$$AIC = 2K - 2\log(\mathscr{L}(\hat{\theta}|y)),$$

where K is the number of estimable parameters (degrees of freedom) and $\log\mathscr{L}(\hat{\theta}|y)$ is the log-likelihood at its maximum point of the model estimated. The constant "2" remains "for historical reasons" (Burnham and Anderson, 2002). Hurvich and Tsai (1989) further refined this estimate to correct for small data samples:

$$AICc = AIC + \frac{2K(K+1)}{n-K-1},$$

where n is the sample size and K and AIC are defined above. If n is large with respect to K, this correction is negligible and AIC is sufficient. $AICc$ is more general, however, and is generally used in place of AIC. The best model is then the model with the lowest $AICc$ (or AIC) score. It is important to note that the AIC and $AICc$ scores are ordinal and mean nothing on their own. They are simply a way of ranking the models.

While AIC is a powerful tool for comparing models, it remained largely unknown in the West for many years due to the fact that the original research and many papers building upon it were written in Japanese and were not quickly translated to English. Burnham and Anderson (2002) provided the first thorough examination of AIC and of information criteria in general and their text is widely regarded as an authority on the subject. AIC is largely used in the biological sciences, specifically in the environmental and marine and watershed sciences. It has remained largely unused outside of this arena, but examples can be found in other fields, including the pharmacological sciences and others. It has seen some use in marketing literature, specifically in a study by Andrew and Currim (2003) where they found it to identify areas of significant improvement in model development. It is at least partially the intention of this paper to introduce AIC techniques to a new audience and area of research.

2.2. Wine and rating

The literature has addressed a wine's status and worth in the literature. For example, there has been evidence showing that the reputation of a wine has a larger impact on its price than its quality does on its price (Landon and Smith, 1998), and though Taylor and Barber (2009) have published findings that rating is an indicator of price, there have been no other studies located that have confirmed the relation to price and ranking by wine critics in the United States.

Horowitz and Lockshin (2002) studied an earlier developed wine-quality evaluation tool to predict retail prices. It was not supportive in finding a strong relationship between wine-quality ratings and price. Significantly, however, was that finding that other factors, such as varietal, production year and area of production did have an influence.

For most consumer goods, a potential purchaser can utilize a lot of tools, including publications like *Consumer Reports* to gain insight in understanding of the products quality, utility and value. However, for wine, a product that cannot be assessed until the buyer purchases it, one can only rely on the subjective opinions of others in making the purchase decision. Therefore, some consumers look for ratings by the *Wine Spectator*, the *Wine Advocate*, the *Wine Enthusiast* and others as a guide for judging quality. This is supported by Roberts and Reagans (2007) who found that when consumers rely on expert judgment, the price for a product is positively correlated to its rating.

The retail price for a wine can differ from retailer to retailer and a positive rating from the *Wine Spectator* affect availability and price nearly immediately. On the flipside, the wholesale price of a wine is generally set at release and tends to be constant with large brand monopolistic distributors tending to dominate the marketplace. Thus, wholesale pricing is less expected to be increased by wine ratings, at least until the winery increases prices for future releases. Further, as restaurants are usually required by state laws to purchase wines from a wholesaler it is more appropriate to focus on the wholesale price for this this study, just as was one in Taylor and Barber (2009). It is essential to appreciate wineries and wholesalers typically have formed a belief about the wine product when they establish their pricing and it can be assumed that there is some commonality in their assessments of quality and those that ultimately get reported by critics such as those in *Wine Spectator* (Roberts and Reagans, 2007).

3. Methodology

Data on the rating, price, grape used, vintage, year rated, and region of production were used. Wholesale pricing data was obtained using the Texas wholesale catalog from the Domaines and Estates division of Glazer's Wholesale, based in Dallas, Texas. Ratings were obtained from the Wine Spectator online wine-rating database (http://www.winespectator.com). The sample size was $n=197$. There were nine regions: California ($n=92$), France ($n=31$), Australia ($n=35$), Italy ($n=23$), New Zealand ($n=5$), Portugal ($n=2$), South America ($n=2$), South Africa ($n=6$), and Germany ($n=1$). There were nine varietals: Cabernet Sauvignon ($n=24$), Syrah ($n=8$), Chardonnay ($n=22$), Other Red ($n=65$), Sauvignon Blanc ($n=10$), Merlot ($n=24$), Other White ($n=20$), Pinot Noir ($n=17$), and Zinfandel ($n=7$). This was in accordance with the precedent set by Taylor and Barber (2009). As stated above, $AICc$ is used in order to determine the best model. Several models are estimated using GLM (identity link function) and their associated $AICc$ scores are calculated; specifically, the following models were estimated:

$$\mathrm{Mo}: \quad rating = \beta_o + \varepsilon$$

$$\mathrm{M1}: \quad rating = \beta_o + \beta_1 price + \varepsilon$$

$$\mathrm{M2}: \quad rating = \beta_o + \beta_1 price + \sum_i \beta_i (region_i) + \varepsilon$$

$$\mathrm{M3}: \quad rating = \beta_o + \beta_1 price + \sum_j \beta_j (varietal_j) + \varepsilon$$

$$\mathrm{M4}: \quad rating = \beta_o + \beta_1 price + \sum_k \beta_k (vintage_k) + \varepsilon$$

$$\mathrm{M5}: \quad rating = \beta_o + \beta_1 price + + \sum_i \beta_i (region_i) + \sum_j \beta_j (varietal_j) + \varepsilon$$

$$\mathrm{M6}: \quad rating = \beta_o + \beta_1 price + \sum_i \beta_i (region_i) + \sum_k \beta_k (vintage_k) + \varepsilon$$

$$\mathrm{M7}: \quad rating = \beta_o + \beta_1 price + \sum_j \beta_j (varietal_j) + \sum_k \beta_k (vintage_k) + \varepsilon$$

$$\mathrm{M8}: \quad rating = \beta_o + \beta_1 price + \sum_i \beta_i (region_i) + \sum_j \beta_j (varietal_j) + \sum_k \beta_k (vintage_k) + \varepsilon$$

where *rating* is the rating of the wine, *price* is the price of the wine, $region_i$ is a set of dummy variables for each region, $varietal_j$ is a set of dummy variables for each varietal, $vintage_k$

is a set of dummy variables for each vintage, and ε is an error term. The β variables are then the estimated coefficients for each parameter.

Each of the models presented above have different numbers of coefficients to estimate, so K will be different for each model, except for Models 2 and 3 and Models 6 and 7; this is simply due to the fact that there are the same number of regions and varietals. Each model will also have a different maximum value of its log-likelihood at its maximum point. This implies that each model should have a different *AICc* score. The eight models were specifically chosen to highlight the effects of having different values for K and different values for the log-likelihood. Mo can be thought of as the *AIC* equivalent of a null-model. Mo states that the value for the rating of a wine is a random process and cannot be predicted. Each of the successive models then includes progressively more information; the models become more complicated. As the number of control variables increases, the level of generality decreases; that is, the greater the number of controls, the more we are simply fitting a model to our specific data as opposed to gaining generalized information on the unknown, hypothetical true model, albeit while gaining an increased measure of fit to the data. If different wines or different years are used, the best model found here may not be the same. What *AIC* accomplishes is establishing the best model for the given data. While the true relationship is impossible to know, the model with the lowest *AIC* score is then the model that best represents the true relationship with the given data. The model with the lowest score then becomes the focus and less so the individual variables.

The following assumptions were made: the models were linear in nature (using a bivariate scatterplot), homoscedasticity of the errors (scatterplot between each independent variable and the dependent variables), and that variables were independent and normally distributed. These assumptions were tested prior to running the regression analysis and the assumptions were confirmed. Regression results were considered significant for $p \leq 0.05$.

AIC methodology requires the calculation of other associated statistics. These statistics, along with the *AIC* and *AICc* results, are presented in Table 1. The equations for these associated statistics are:

$$\Delta AICc = AICc(i) - AICc_{min}$$

$$\text{Akaike Weight}: w_i = \frac{\exp(-\frac{1}{2}\Delta AIC_{c,i})}{\sum_{r=1}^{R}\exp(-\frac{1}{2}\Delta AIC_{c,r})}$$

$$\text{Evidence Ratio}_i : (ER_i) = \frac{w_{best}}{w_i}$$

$$\text{Log}_{10}(ERi) : LER_i = \log_{10}(ER_i),$$

where $AICc(i)$ is the individual *AICc* score for each model, $AICc_{min}$ is the minimum *AICc* score of the models tested (or the *AICc* score for the best model), R is the number of models, r is the model being considered, w_{best} is the weight of the best model, and w_i is the weight of the other individual models. The weight, w_i is considered the weight of evidence in favor of a model being the actual best model for the given data, given that one of the models must be the best model. Note that the weights of all models summed together equals one. The evidence ratios, ER_i, is the relative likelihood of a pair of models, representing the evidence about fitted models as to which is better in an information criteria sense.

Following Kass and Raftery (1995), *a priori*, we decided to use the terms 'minimal', 'substantial', 'strong', and 'decisive' to correspond approximately to *LER*s between model probabilities of greater than 0, 0.5, 1, and 2 respectively. R version 3.0.1 was used in the analysis.

Table 1
Summary of *AIC* results for models relating the rating of the wine and control variables.

Model	*df*	*AIC*	*AICc*	*ΔAICc*	w_i	ER_i	LER_i
Mo	2	1140.64	1140.70	31.60	1.15e−7	7,266,648	6.86
M1	3	1122.85	1122.98	13.88	8.16e−4	1030.27	3.01
M2	11	1128.52	1128.94	20.84	2.51e−5	33,491.88	4.52
M3	**11**	**1107.68**	**1109.10**	**0.00**	**8.41e−1**	**1**	**0**
M4	12	1127.21	1128.91	19.81	4.20e−5	20,003.51	4.30
M5	19	1108.21	1112.51	3.40	1.53e−1	5.48	0.74
M6	20	1133.79	1138.56	29.46	3.37e−7	2,495,165	6.40
M7	20	1114.67	1119.44	10.34	4.77e−3	176.13	2.25
M8	28	1115.35	1125.02	15.92	2.94e−4	2858.06	3.46

4. Results

Model 3 received the lowest *AICc* score ($AICc = 1109.10$), indicating that this model is the most parsimonious model for the given data. There is decisive evidence in favor of model 3 relative to the other models ($LER_i > 2$), with the exception of model 5; there is substantial evidence in favor of model 3 relative to model 5 ($LER = 0.74$). Model 3 received 84% of the total weight of the models considered.

Once the best model is established, one can use the traditional null-hypothesis testing for the given best model in order to establish the scale of the relationship between the variables. This is the same as what is normally presented in regression analysis. Table 2 provides the regression results for model 3. Zinfandel was the reference group. As seen in Table 2, there is a significant positive relationship between price and rating, indicating that as the price of the wine increases, its rating increases.

5. Discussion

As is seen in Table 1, there is almost zero support for model Mo being the best model. Recall that model Mo is the model that estimates the rating for a wine assuming that the rating is random. The fact that there is almost zero support for this model indicates that the rating for a wine can be estimated from other variables.

Model 3 was the best model for the given data. Model 3 modeled the rating of a wine on its price and the varietal of the wine. This implies that both price and varietal are important in

Table 2
Summary of estimates for model 3.

Variable	*Coefficient*
Price	0.04***
Cabernet Sauvignon	−2.36
Syrah	1.44
Chardonnay	3.61*
Other Red	0.60
Sauvignon Blanc	0.31
Merlot	2.35
Other White	0.27
Pinot	1.71

$^{**}p < 0.01$.
$^{*}p < 0.05$.
$^{***}p < 0.001$.

estimating the rating of a wine and should be included in any regression or other type of analysis performed on wine ratings. The other models either omitted varietal or included other variables along with varietal. The fact that these other models received higher *AICc* scores indicates that the controls in these models are less important than varietal (or not important at all) in modeling a wine's rating, given this data. Although not necessary once the best model is established, the other models were examined. As expected given the *AICc* scores for those models, the coefficient estimates for all the dummy variables for region and vintage were insignificant. What this indicates is that adding the additional region and vintage dummies did not increase the maximum likelihood of the function enough to counter the effects of the increase in the number of estimated variables. The relatively simple model that included only price and varietal information, as indicated by their degrees of freedom, was the best model for the given data. Model 3 can then be considered the best representation of the unknown, hypothetical true model for determining a wine's rating.

Given that there is an estimable relationship between ratings and the control variables, model 3 was determined to be the best model. In model 3, the scale of the relationship can be determined. As noted above, there is a significant positive relationship between price and rating, indicating that as the price of the wine increases, its rating increases. As has been previously suggested, wineries spend tremendous amounts of resources to create premium wines. It therefore is fully fathomable that a wine that has been "designed" to be of high quality, would have a higher price and that once it is subjectively evaluated by a wine expert, it would have a higher rating (Taylor and Barber, 2009).

While these findings do confirm the findings of Taylor and Barber (2009); this study used a different model from the analysis presented here and their coefficient estimates are thus different. Only one of the variables for varietal was significant: Chardonnay. There is a significant positive relationship, indicating that Chardonnays tend to be rated slightly higher relative to the other wines tested. This is a very interesting finding that was not previously identified by Taylor and Barber (2009). The reason for this is also not clear to the researchers. It could be that Chardonnay wines that are reviewed are of better quality, or that they are less complex or open to less scrutiny by critics.

Ordinarily, once the best model is established, the other models can be effectively ignored. However, models 3 and 5 were somewhat close in their *AICc* scores. As *AIC* may be unfamiliar to some, a comparison of models 3 and 5, 7, and 8 yield some interesting results and differences between the models. The only difference between the models is the number of coefficients to be estimated: model 5 contained more variables than did 3. The same is true for models 3 and 7 and 8. Models 3, 5, 7, and 8 all contain information on the price and varietal of the wine; models 5, 7, and 8 contain additional information. However, this additional information is not as useful in the model, as indicated by their higher *AICc* scores. The increase in the degrees of freedom outweighs any additional gains from including this additional information. This implies that the additional information contained in these models decreases the quality of the model by introducing trivial information and increasing the number of coefficients to be estimated. Model 3 is then the model that best balances the quality of the information included in the model with the information lost by introducing unnecessary variables. Model 3 is then the model that best represents the hypothetical true model given the data and is the model that should be used when determining the relationship between price and rating. The other models can be effectively ignored.

One drawback that is common to all forms of statistical analysis is omitted variable bias. While a best model was found and a relationship between the price and rating of a wine was estimated, it is certainly possible that other variables could influence the rating of a wine and should be included in any regression equations estimated. However, changing the number of estimators would then change their *AICc* scores and thus the best model may change. Calculating *AICc* scores for those models that include the new information would then also need to occur before discussing relationships between specific variables.

6. Implications for estimate parameters and the wine industry

6.1. AIC as an improvement for methodology and coefficient estimates

As Burnham and Anderson (2002) note, once the most parsimonious model is established, traditional statistical inference can then be based on this model. As *AIC* is a tool that compares different models given the same data, each model estimated will generate different error terms, or residual sum of squares (*RSS*) values. This in turn will affect the significance of the coefficients estimated in each model and the different model specifications may slightly change the values of the estimates themselves. This is not necessarily a problem, however, given that only the coefficients taken from the winning model are of interest; the other estimates from the other models can effectively be ignored. Nonetheless, the estimates from the winning model are subject to the same benefits, limitations, and problems from estimation as they would be if *AIC* had not been used.

Where *AIC* does improve upon other methodologies is in the quality of the model used for null hypothesis testing and the resulting improvement in the coefficient estimates. This has partly been discussed above, in that *AIC* indicates the model that best balances increases in the information gained versus uncertainty in the coefficient estimates that comes from increasing the number of parameters estimated and thus establishes a best model. This, however, is not the only benefit accrued from using *AIC*.

It can be argued that reality is infinitely dimensional and no model will ever completely capture the true relationship between two variables. In that sense, every model is effectively wrong; as the mathematician George Box stated: “Essentially, all models are wrong, but some are useful,” (Box and Draper, 1987). If reality cannot ever be fully modeled, the question arises as to what model best reflects reality given the sample data. Here, model M3, and its estimated coefficients, are the best model and estimates that map the true relationship between price and rating given the data. In that sense, they are the best estimates and are the most accurate estimates of reality that can be hoped for. This would allow for better, more accurate planning from a business standpoint. As the estimates generated are the estimates that best reflect reality, the use of these estimates would presumably be the best and most useful for general business planning.

From a less philosophical approach, *AIC* tells us what variables are important and which are not in establishing a model. If a variable appears in a model that has a higher *AIC* score than a model that does not contain that variable, that variable can be ignored. Variables that appear in the winning model are the most important ones for modeling reality given the sample data. In this study, the varietal was found to be important, while the region and vintage were not. Given the sample used here, only varietal adds important information in establishing a model between price and rating; the other variables can be ignored. By decreasing the number of coefficients estimated, the efficiency of the remaining coefficients increases (Burnham and Anderson, 2002).

Again, from a usefulness standpoint, the use of *AIC* requires calculating the maximum likelihood (ML). The residual variance must also be calculated ($\hat{\sigma}$). The ML estimator of $\hat{\sigma}$ is $\hat{\sigma} = RSS/n$, which differs from the least squares (LS) estimate by a factor of $n/(n-(r+1))$, where RSS is the residual sum of squares, n is the sample size and r is the number of coefficients estimated. The log-likelihood function can then be written as

$$\log(\mathscr{L}(\hat{\theta})) \approx -\tfrac{1}{2} n \log(\hat{\sigma})^2.$$

This is important because, as Burnham and Anderson (2002) show, it “allows a simple mapping from LS analysis into the maximized value of the log-likelihood function for comparisons over linear models with normal residuals”. When predictor variables that are found to be not important are included in the model, the estimate of $\hat{\sigma}$ is negatively biased and precision is exaggerated; that is, as the number of coefficients estimated (r) goes up, the standard errors go down, which may bias the significance of the estimates. *AIC* methodology reduces this bias and improves the log-likelihood estimates.

7. Conclusions and future research

The first question that must be asked of any research that follows so closely the methodology of a previous study is whether the new research adds anything new to the discussion. The researches argue that the use of *AIC* in finding the best model fit does indeed add a very interesting idea to the world of wine research. As *AIC* has not been previously used, this in itself lends a very interesting contribution to the literature. Secondarily, it confirms that price and rating are related, confirming Taylor and Barber (2009).

From the standpoint of *AIC*, the most parsimonious model was found to be a model that included information on the price of the wine and the varietal. Information pertaining to the vintage or the region of production was unnecessary. As the goal of *AIC* is to balance both the fit of the model to the data with any information lost by including more variables, this result shows that a complex model is not always needed; indeed, a complicated estimable model may actually decrease the usefulness of the model. A simple model that contains the most useful model is often best.

For restaurants and retailers determine which wines to purchase and how to price them, is a difficult and costly proposition. Further, question of whether the rating makes a real difference can linger and a decision makers mind. These results measure how the grape type can affect wine wholesale prices. These results re-confirm that the critical expert review can have an impact on price and possibly as an indicator of quality, which is what ratings are typically seen as by the consumer.

Lastly, a new question is raised through the discovery that, while wine rating and price are positively related, Chardonnays tend to be rated slightly higher relative to the other wines tested. It would only be presumptuous and speculative to attempt to explain this, but it does lend itself to be pursued as a future research project. Secondarily, as suggested by Taylor and Barber (2009), other rating systems and consumer outlets for information gathering on quality should be looked at to see if the same results are observed.

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