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Identifying the Effects of Objective and Subjective Quality on Wine Prices*

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Abstract

This study examines a framework developed by Cardebat, Figuet, and Paroissien in a 2014 *Journal of Wine Economics* article for identifying the impacts of both objective and subjective quality on wine prices. We recognize how various specifications are observationally equivalent and that the interpretation of model estimates depends crucially on the posited assumption for the relation between price and objective and subjective quality. The proposed framework is applied to Australian premium wines. Results indicate that the price impact of expert personal opinions is similar to the impact of objective quality as estimated via weather, vintage, and producer fixed effects. The relative importance of objective quality compared with subjective quality depends crucially on the ability of expert scores to accurately reflect objective quality. (JEL Classifications: C21, Q11, Q54)

Keywords: wine prices, wine quality, expert ratings.

I. Introduction

A substantial literature exists on modeling wine prices. A key feature of these models relates to the notion of wine quality and how it influences prices. Some authors suggest that wine quality is fundamentally determined by the intrinsic factors that lead to the wine's composition (see, e.g., Ashenfelter, 2008; Cardebat, Figuet, and Paroissien, 2014; Ginsburgh, Monzak, and Monzak, 2013). Effectively, the wine's quality is determined by a series of vineyard and wine-making practices/attributes and climatic variables. Viewed in this light, measures of wine quality based on the factors that impact on the production of a wine can be termed as "objective" measures of wine quality.

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In the bulk of the hedonic wine price literature, quality scores from experts are typically used as a measure of a wine's quality. As has been demonstrated by a number of studies (Ashton, 2012, 2013; Cardebat and Paroissien, 2015; Masset, Weisskopf, and Cossutta, 2015; Stuen, Miller, and Stone, 2015), however, expert ratings typically differ for the same wine. This recognition suggests that no single-expert rating (or group of ratings) can be viewed as a unique and perfect measure of wine quality. In essence, each taster brings his or her own "preferences and prejudices" to the judgment of wines. Viewed in this light, measures of wine quality based on expert ratings can be termed as "subjective" measures of wine quality.

Only a few studies have explicitly recognized the subjective biases of experts in hedonic price models. Oczkowski (2001) assumes that prices are determined by some notion of latent quality that is reflected by a number of different expert ratings. Employing an instrumental variable estimator permits the consistent estimation of the relation between latent quality and price. Lecocq and Visser (2006) correct for expert measurement errors by employing an estimate of the variance of expert scores in an expression that corrects for attenuation bias. The recognition of subjective bias leads to an upward correction for the estimate of the impact of quality on price. A deficiency of both these approaches is that only latent quality is assumed to directly influence price; the direct influence of expert opinions on prices is not explicitly recognized. Further, neither of these studies measure the notion of objective quality through the use of wine production factors.

More recently, Dubois and Nauges (2010) and Cardebat, Figuet, and Paroissien (2014) have attempted to recognize the direct impact of both objective and subjective quality on wine prices. In part, these studies seek to determine the relative importance of these two measures of quality on prices. A key question addressed by these studies is, do the intrinsic fundamentals governing wine production influence price more than the subjective opinions of experts?

The purpose of this study is to examine and unpack the model structure employed by Cardebat, Figuet, and Paroissien (2014). The examination shows that the conclusions reached by Cardebat, Figuet, and Paroissien (2014) on the relation between quality and Bordeaux wine prices depend crucially on the assumed model specification. We demonstrate how different specifications may potentially lead to alternative conclusions about the relative impact of objective and subjective quality on prices. We then apply the proposed framework to Australian premium wines. The application usefully illustrates the importance of the degree of the expert taster's measurement error in influencing the relative importance of subjective and objective quality on prices.

II. Conceptual and Modeling Framework

The framework assumes that there exists some underlying objective notion of wine quality, which is not observed directly but can be reflected by a series of weather variables and winery-specific vineyard and wine-making practices/attributes. This premise is fundamentally consistent with the literature in viticulture and oenology (see, e.g., Reynolds, 2010a, 2010b). These supply-side practices and attributes that enhance quality invariably cost more to implement, and hence the motivation for including objective quality in a hedonic wine price function is established.

From the demand side, the hedonic price literature demonstrates that subjective expert quality ratings moderately correlate with prices over numerous studies (for a meta-analysis, see Oczkowski and Doucouliagos, 2015). An interpretation of this consistent finding is that the chosen expert rating may provide some indication of objective quality but also includes the subjective biases of the expert. Some consumers may employ these ratings when making purchase decisions, which in turn influences prices. This motivates the inclusion of a subjective quality expert rating in hedonic price functions.

In the tradition of Dubois and Nauges (2010) and Cardebat, Figuet, and Paroissien (2014), and unlike most previously employed hedonic estimates, the proposed model captures both these fundamental elements of objective and subjective quality in determining prices. We present a series of models to analyze and examine the framework advocated by Cardebat, Figuet, and Paroissien (2014):

$$P_i = \gamma_a Q_i + \theta_a \varepsilon_i + \beta' x_i + u_i \tag{1a}$$

$$P_i = \gamma_b Q_i + \theta_b S_i + \beta' x_i + u_i \tag{1b}$$

$$P_i = \gamma_c S_i + \theta_c \varepsilon_i + \beta' x_i + u_i \tag{1c}$$

$$S_i = Q_i + \varepsilon_i \tag{2}$$

$$Q_i = \alpha' w_i \tag{3}$$

where P is the (log) price; Q is objective wine quality; S is the expert quality score; ε is the difference between the expert quality score S and objective quality Q and is referred to as the personal opinion of the expert by Cardebat, Figuet, and Paroissien (2014); x represents additional price-influencing regressors; w represents regressors that determine objective quality; ε and u are random error terms with $\varepsilon_i \sim IID(0, \sigma_\varepsilon^2)$ and $u_i \sim IID(0, \sigma_u^2)$, with ε being the random error made by the expert in measuring Q, with $\mathrm{cov}(Q,\varepsilon) = 0$. Equations (1a), (1b), and (1c) outline three alternative models that have been advocated or employed to permit both objective and subjective quality to influence prices; these alternatives will be discussed in detail. Equation (2) represents the standard latent variable specification where the observed variable (S) is equal to its latent counterpart (Q) and a measurement error (ε). Equation (2) is typically used to set the metric in latent factor measurement models; see, for example, Bollen (1989, p. 240) and Oczkowski (2001) in the hedonic wine price context.

To estimate the system described by equations (1) to (3), we need to recognize that Q and ε are unobserved and need to be estimated. Substitute equation (3) into equation (2) to get

$$S_i = \alpha' w_i + \varepsilon_i. \tag{4}$$

Estimating equation (4) by least squares identifies $\widehat{Q_i} = \hat{\alpha}' w_i$ and $\widehat{\varepsilon_i} = S_i - \widehat{Q_i}$. These predictions can be used in equations (1a) to (1c) to write the following:

$$P_i = \gamma_a \widehat{Q_i} + \theta_a \widehat{\varepsilon_i} + \beta' x_i + u_i, \tag{5a}$$

$$P_i = \gamma_b \widehat{Q_i} + \theta_b S_i + \beta' x_i + u_i, \tag{5b}$$

$$P_i = \gamma_c S_i + \theta_c \widehat{\varepsilon_i} + \beta' x_i + u_i. \tag{5c}$$

Equations (5a) to (5c) contain generated regressors $\hat{Q}$ and $\hat{\varepsilon}$, and applying least squares results in consistent parameter estimates but inaccurate standard error estimates (McKenzie and McAleer, 1997). For their model, Cardebat, Figuet, and Paroissien (2014) employ a bootstrap procedure to estimate accurate standard errors.

We now allude to the relationship between the presented structure and the models employed by Dubois and Nauges (2010) and Cardebat, Figuet, and Paroissien (2014). Dubois and Nauges (2010) employ equation (1b); however, their empirical model does not employ equation (2) and primarily focuses on the role of previous information in determining quality. Unobserved quality is assumed to follow a first-order Markov process, and expert scores are assumed to be a function of unobserved quality and previous expert scores. These assumptions may imply that the advocated approach is not widely applicable.

In contrast, Cardebat, Figuet, and Paroissien (2014) employ equations (1a), (1c), (2), and (3). Two cases are identified, single expert and multiexpert. In the single-expert case, equation (1c) is employed. In the case where a number of different expert scores are employed, $\hat{Q}$ and $\widehat{\varepsilon_j}$ (j counts across different experts) are used as regressors; this is a generalized version of equation (1a).

It is important to note that given equation (2), the three price model equations (i.e., equations 1a, 1b, and 1c) are observationally equivalent. The observed data cannot distinguish between the models. Effectively, only one of these equations needs to be estimated to derive the estimates for the other models. The same goodness of fit, residuals, predictions, and standard error estimates are gained from estimating only one model. As a consequence, a choice between models cannot be made using goodness of fit and related measures. Importantly though, the substantive economic interpretation of estimates depends crucially on the posited specification.

First, it is not clear how equation (1c) can usefully identify the impact of objective quality on prices given that Q is not directly employed as a regressor. This recognition diminishes the usefulness of equation (1c). In contrast, both equations (1a) and

(1b) employ Q to identify the impact of objective quality but differ in the measure of subjective quality. Equation (1a) employs the "personal opinion" of the expert (ε), whereas equation (1b) employs the expert score (S). Equation (1a) allows us to determine the additional impact that the expert may have over and above objective quality on price. By design, its regressors are uncorrelated, $\mathrm{cov}(Q, \varepsilon) = 0$, and so the influence of objective quality and the unique additional impact of the expert on prices can be uniquely assessed. Essentially, $\widehat{\theta_a}$ captures the impact of the expert through ε on price, recognizing that the impact of Q (also contained in S) on prices already occurs through $\widehat{\gamma_a}$.

Equation (1b) appears to be a natural specification given that both objective and subjective quality are hypothesized to influence wine prices; this is employed by Dubois and Nauges (2010). Both Q and S are measures of wine quality—the former being objective, and the latter subjective. However, once equation (1b) is combined with equation (2), its appeal diminishes. Given equation (2), it appears that equation (1b) will artificially overstate the impact of subjective quality on prices as the S regressor also includes Q. Effectively, $\widehat{\gamma_b}$ captures the influence of Q on price, but $\widehat{\theta_b}$ also captures the influence of Q and, additionally, ε on price. In other words, $\widehat{\theta_b}$ may be larger than $\widehat{\gamma_b}$, as both associated regressors include Q, but additionally, $\widehat{\theta_b}$'s regressor also includes ε, which is expected to positively impact on price.

Interestingly, the likely dominance of subjective over objective quality in equation (1b) is manifested not through a higher $\widehat{\theta_b}$ but a lower $\widehat{\gamma_b}$. To see this, using equations (1a), (1b), and (2), we get $\widehat{\gamma_b} = \widehat{\gamma_a} - \widehat{\theta_a}$ and $\widehat{\theta_b} = \widehat{\theta_a}$. This shows how the objective quality estimate for equation (1b) is reduced from that for equation (1a) by the unique additional impact of personal opinion or the subjective impact in equation (1b). In fact, for $\widehat{\gamma_b} > \widehat{\theta_b}$ to occur in equation (1b), the following must hold: $\widehat{\gamma_a} > \widehat{2\theta_a}$. That is, for objective to exceed subjective impact for equation (1b), the objective impact in (1a) needs to be more than twice the size of personal opinion in equation (1a).

This discussion illustrates the important role of equation (2) in the economic interpretation of model estimates. As suggested, given equation (2), subjective quality as measured by S is likely to exceed Q in determining prices. Thus, the following question is likely to be answered in the affirmative, by construction: do expert quality ratings dominate the influence of wine-making fundamentals in influencing prices? The more relevant and interesting question is, therefore, are the opinions of experts as they differ from the wine production fundamentals more important than the fundamentals in determining prices? This latter question can be assessed by equation (1a).

To illustrate the importance of the assumed price-quality specification, consider the three alternative models and the estimates from the single-expert case of Cardebat, Figuet, and Paroissien (2014, equation 5, p. 289) and equations (1c) and (5c). Employing equations (1) and (2), the relation between the estimates can be written as follows: $\widehat{\gamma_b} = -\widehat{\theta_c}$ and $\widehat{\theta_b} = \widehat{\gamma_c} + \widehat{\theta_c}$, and $\widehat{\gamma_a} = \widehat{\gamma_c}$ and $\widehat{\theta_a} = \widehat{\theta_c} + \widehat{\gamma_c}$. Table 1 uses these relations to interpret the single-expert estimates in Cardebat, Figuet, and Paroissien (2014, table 7, p. 298) in terms of the alternative model equations (1a) and (1b).

In Table 1, $\widehat{\gamma_c} > \widehat{\theta_c}$ occurs for all single experts and an average score. In part, this led Cardebat, Figuet, and Paroissien (2014) to conclude that "prices are influenced more deeply by the fundamental quality of the wines than they are by the judge's subjectivity" (p. 282). As previously indicated, given that equation (1c) does not directly employ Q, it is not clear how $\widehat{\gamma_c}$ can represent a measure of the impact of objective quality. In contrast, for both equations (1a) and (1b), the estimates imply that $\widehat{\theta_a} > \widehat{\gamma_a}$ and $\widehat{\theta_b} > \widehat{\gamma_b}$, which suggests that the subjective price impact coefficient is greater than the objective impact coefficient. For equation (1b), the objective estimates are negative ($\widehat{\gamma_b} < 0$) and, as expected, much lower than the subjective estimates. For equation (1a), $\widehat{\theta_a} > \widehat{\gamma_a}$, which suggests that prices may be determined more by the personal opinion of the taster than the fundamentals. It is not clear, however, that these estimates are directly comparable given that $\hat{Q}$ and $\hat{\varepsilon}$ have different means and standard deviations. A more definitive statement for equation (1a) could be made by evaluating the so-called standardized beta estimates (Wooldridge, 2006, pp. 195–196). For equation (1a), the beta coefficients are $\widehat{\gamma_a^*} = \left(\frac{\widehat{\sigma_{\hat{Q}}}}{\widehat{\sigma_p}}\right)\widehat{\gamma_a}$ and $\widehat{\theta_a^*} = \left(\frac{\widehat{\sigma_{\hat{\varepsilon}}}}{\widehat{\sigma_p}}\right)\widehat{\theta_a}$. Even though $\widehat{\theta_a} > \widehat{\gamma_a}$, the relation between the corresponding beta coefficients depends on $\widehat{\sigma_{\hat{Q}}}$ and $\widehat{\sigma_{\hat{\varepsilon}}}$, which are not provided in the article.

III. Data and Model

To further illustrate the usefulness of the model defined by equations (1) to (5), we apply the technique to Australian premium wines. For reasons articulated previously, the preferred specification employs equations (1a) and (5a). We use quality scores developed by Halliday (2014) that relate to a cross section of wines evaluated in early 2014 and available in the market at 2014 prices in Australian dollars (AUD). The use of a single-year data set avoids any possible inconsistency of tasters' evaluations over time. Following Cardebat, Figuet, and Paroissien (2014), we consider three sets of variables for determining objective quality (w in equation 3): weather variables, time (vintage of wine), and fixed effects for the influence of producers. It is argued that in part these variables determine the intrinsic quality of wine. For weather, we use rainfall and temperature data as identified and employed by Oczkowski (2016). The vintage variable captures the impact of quality improvements due to technological and other advances over time, and producer fixed effects captures a series of factors unique to each producer, such as soil types, vine exposure, use of irrigation, fertilizer application, maturation techniques, storage facilities, and so forth.

Table 1
Objective and Subjective Quality Effects on Bordeaux Wine Prices

	$\hat{P}_i = \widehat{\gamma_a}\widehat{Q_i} + \widehat{\theta_a}\widehat{\varepsilon_i}$		$\hat{P}_i = \widehat{\gamma_b}\widehat{Q_i} + \widehat{\theta_b}S_i$		$\hat{P}_i = \widehat{\gamma_c}S_i + \widehat{\theta_c}\widehat{\varepsilon_i}$	
Expert score	$\widehat{\gamma_a}$	$\widehat{\theta_a}$	$\widehat{\gamma_b}$	$\widehat{\theta_b}$	$\widehat{\gamma_c}$	$\widehat{\theta_c}$
Average score	0.170	0.204	−0.034	0.204	0.170	0.034
International Wine Cellar	0.183	0.260	−0.077	0.260	0.183	0.077
Jancis Robinson	0.128	0.135	−0.007	0.135	0.128	0.007
Wine Advocate	0.109	0.157	−0.048	0.157	0.109	0.048
Wine Spectator	0.088	0.120	−0.032	0.120	0.088	0.032

Notes: The two columns under the left-most equation are implied by equation (1a), and the two columns under the middle equation are implied by equation (1b). The two columns under the right-most equation are from Cardebat, Figuet, and Paroissien (2014, table 7, p. 298).

In terms of equation (4), we specify the following:

$$S_i = \alpha_0 + \alpha_1(Rain)_i + \alpha_2(Diff)_i + \alpha_3(Temp)_i + \alpha_4(Temp)_i^2 + \delta\,(Vintage)_i + \pi'(Prod_{id})_i + \varepsilon_i, \quad (6)$$

where S is the quality rating (out of 100) accessed from Halliday (2014). Motivation and definitions for the specific weather variables are from Oczkowski (2016): *Rain* is the average monthly rain (milliliters) during the harvest months (January to March); *Diff* is the average difference between the maximum and minimum temperatures (degrees Celsius) over the growing season (October to March); and *Temp* is average temperature over the growing season based on monthly averages (October to March). A quadratic specification for growing season temperature is employed, and for the Australian climate, the expected coefficient signs are $\alpha_3 > 0$ and $\alpha_4 < 0$; the optimal growing season temperature is $-\alpha_3/2\alpha_4$. *Vintage* is the year in which the grapes were harvested, and $Prod_{id}$ is a series of dummy variables identifying each individual producer.

For modeling wine prices, we employ the standard log-linear form and specify equation (5a) as follows:

$$\ln(Price)_i = \beta_0 + \gamma_a\widehat{Q_i} + \theta_a\hat{\varepsilon}_i + \beta_1(Vintage)_i + \beta_2'(Region)_i + \beta_3'(Variety)_i + u_i, \quad (7)$$

where *Price* is the recommended retail price in 2014 measured in AUD (Halliday, 2014); $\hat{Q}$ and $\hat{\varepsilon}$ are predictions and residuals, respectively, from equation (6); *Region* is a series of dummy variables depicting the region from which the grapes were sourced; and *Variety* is a series of dummies representing the variety, blend, or style of wine. The employed variables have been identified as important price determinants in previous Australian studies (see, e.g., Schamel and Anderson 2003).

To facilitate meaningful estimation, the sample of wines was restricted to vintage wines from single regions (no multiregion blends). $Prod_{id}$, regions, and varieties/styles were only included if each category had at least 10 wines; no residual categories for other wines were employed. The restriction for $Prod_{id}$ and identifying fixed effects is important because too many fixed effects (of small size) can have serious consequences for the efficiency of estimates due to issues of multicollinearity and loss of degrees of freedom (see Nelson and Kennedy 2009). These selections reduce the sample size to 2,469 wines, which prohibits a meaningful use of an individual variety/style approach for identifying weather effects as in Oczkowski (2016). Effectively, the model estimates average weather effects across all wines; this approach was also employed by Cardebat, Figuet, and Paroissien (2014).

Descriptive statistics for the data are presented in Table 2. In summary, wines come from nine vintages produced by 175 wineries that make on average 14.3 wines. Thirty-six regions are covered with the most dominant being Margaret River ($n = 344$), McLaren Vale ($n = 326$), and Barossa Valley ($n = 266$). Wines from 32 varieties/styles are examined with the most dominant being Shiraz ($n = 561$), Chardonnay ($n = 343$), and Cabernet Sauvignon ($n = 273$).

IV. Results

The estimates for equation (6) are presented in Table 3. Robust standard errors, which recognize cluster error correlation due to producer effects, are employed. To illustrate the impact of producer fixed effects and vintage on estimates of objective quality, three alternative models for expert ratings are presented. Table 3 illustrates how weather variables only explain 3.3% of the quality score when weather effects are averaged across all wines of different types. This low level of explanatory power is comparable to some previous estimates for individual varieties (Shiraz and Riesling) and is consistent with the notion that weather has a much weaker influence on quality in an Australian context compared with some European countries (see Oczkowski 2016). Based on the model for weather variables only, the optimal estimated average growing temperature is 17.7 °C. Vintage adds approximately 3% additional explanatory variation for the quality score. In stark contrast, producer effects explain an additional 29% of the score variation. Even though the growing season temperature variables are statistically significant in all models, harvest rainfall loses it statistical importance in the fixed effects model possibly due to multicollinearity effects from the introduction of an additional 174 producer-identifying regressors.

The estimates of equation (7), which seek to identify the individual objective and personal opinion quality effects on price, are presented in Table 4. The presented results relate to the same price-determining regressors but differ in terms of the estimates for $\hat{Q}$ and $\hat{\varepsilon}$ from Table 3 and equation (6). Cluster robust errors are presented and contrasted with those based on the paired bootstrap to recognize the potential effects of the generated regressors $\hat{Q}$ and $\hat{\varepsilon}$. The results for the region and variety/style variables are suppressed. It is clear that irrespective of which model is employed, $\widehat{\gamma_a} > \widehat{\theta_a}$; that is, the estimate for objective quality exceeds the personal

Table 2
Descriptive Statistics

	Mean	*Standard deviation*	*Minimum*	*Maximum*
Price	33.58	23.35	7.0	325.0
Ln(price)	3.358	0.525	1.946	5.784
Score	91.82	3.273	83	99
Vintage	2011.9	1.165	2005	2013
Harvest rain	41.64	34.01	1.733	215.1
Temperature difference	12.60	1.950	5.667	17.98
Growing season temperature	19.17	1.503	15.20	23.99

Note: N = 2,496 encompassing 175 producers, 36 regions, and 32 varieties/styles.

Table 3
Wine Score Estimates

	Weather variables only	*Weather and vintage*	*Weather, vintage, and producer fixed effects*
Harvest rain	−0.007*	−0.007*	−0.006
	(−2.12)	(−2.01)	(−1.20)
Temperature difference	−0.074	−0.053	−0.037
	(−1.29)	(−0.88)	(−0.37)
Growing season temperature	2.910*	3.046*	3.551*
	(2.29)	(2.46)	(2.68)
Growing season temperature^2	−0.082*	−0.085*	−0.093*
	(−2.47)	(−2.65)	(−2.74)
Vintage		−0.446*	−0.526*
		(−6.08)	(−7.29)
Constant	67.45*	962.6*	1119.2*
	(5.53)	(6.57)	(7.83)
R^2	0.033	0.058	0.344
$\widehat{\sigma}_\varepsilon$	3.222	3.180	2.752
$N - k$ (degrees of freedom)	2,491	2,490	2,316

Notes: The asterisk denotes statistical significance at the 5% level. Cluster robust t-ratios are presented in parentheses. N = 2,496 with 175 wine producers.

opinion estimate. Objective quality and personal opinion are statistically significant in all models. Results suggest that a 1-point increase in the personal opinion (the difference between score and objective quality) raises prices by approximately 8% on average.

A more appropriate comparison of the differential quality effects may be made by comparing beta estimates, which are also presented in Table 4. For all models, $\widehat{\theta_a^*} > \widehat{\gamma_a^*}$, which suggests that in standardized terms, the impact of personal opinion exceeds objective quality. For the best-fitting fixed effects model, however, there is little difference between the beta estimates.

Table 4
Wine Price Estimates

	First-stage models		
	Weather variables only	*Weather and vintage*	*Weather, vintage, and producer fixed effects*
Objective quality ($\widehat{\gamma_a}$)	0.1367	0.1306	0.0990
	(2.31)	(2.08)	(12.96)
	[2.55]	[2.30]	[12.04]
	{0.1544}	{0.1957}	{0.3618}
Personal opinion ($\widehat{\theta_a}$)	0.0821	0.0821	0.0758
	(20.37)	(20.38)	(19.17)
	[21.20]	[21.20]	[19.76]
	{0.5033}	{0.4966}	{0.3827}
Vintage	−0.1157	−0.0943	−0.1099
	(−12.25)	(−3.33)	(−11.35)
	[−12.25]	[−3.51]	[−11.35]
Constant	223.6	181.09	215.31
	(11.56)	(2.90)	(11.04)
	[11.15]	[3.08]	[11.02]
R^2	0.567	0.566	0.570

Notes: All presented estimates are statistically significant at the 5% level. Cluster robust *t*-ratios are presented in parentheses. Bootstrap cluster robust *t*-ratios are presented in brackets. Standardized beta coefficients are presented in braces. $N = 2{,}496$. Regressions also contain 35 region and 31 variety/style variables.

There are a number of other noteworthy features of the results in Table 4. Bootstrap standard errors do not vary greatly from their cluster robust counterparts. The vintage effect is significant and important in all models illustrating a per annum price effect of approximately 10%. It appears that the precision in estimating S in the first-stage regression equation (i.e., equation 6) impacts most on the estimates for objective quality, $\widehat{\gamma_a}$, whereas the other estimates are relatively stable. For the models without fixed effects, where the R^2 values are low for the measurement equation (i.e., equation 6), or measurement error variance ($\widehat{\sigma_\varepsilon^2}$) is high, $\widehat{\gamma_a}$ is estimated relatively imprecisely resulting in *t*-ratios of approximately 2. In contrast, for the fixed effects model, where the R^2 is much higher ($\widehat{\sigma_\varepsilon^2}$ lower), $\widehat{\gamma_a}$ is estimated with greater precision, and *t*-ratios are approximately 12. Note that when examining the point estimates, $\widehat{\gamma_a}$ falls as measurement error falls. This change in point estimates is reversed, however, when beta estimates are examined. The ratio of the beta estimates $(\widehat{\gamma_a^*}/\widehat{\theta_a^*}) = (\widehat{\sigma_{\hat{Q}}/\sigma_{\hat{\varepsilon}}})(\widehat{\gamma_a}/\widehat{\theta_a})$ increases as measurement error variance reduces; in our case, $\widehat{\gamma_a^*}$ approaches $\widehat{\theta_a^*}$ as $\widehat{\sigma_{\hat{\varepsilon}}}$ falls.

V. Conclusion

This study examined empirical approaches that permit both objective and subjective quality to impact on wine prices. The proposed specification, through the use of beta-

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standardized coefficients, allows us to make statements about the relative price impact of objective quality and subjective quality. For a sample of Australian premium wines, the price impact of expert personal opinions is similar to the impact of objective quality as estimated via weather, vintage, and producer fixed effects.

For the preferred specification, it appears that the comparison of objective and subjective quality price impacts may depend crucially on the precision of the expert scores in reflecting objective quality. The highest degree of statistical precision in estimating the impact of objective quality occurs with the inclusion of producer effects, which explains an additional 29% of the variation in score. Further, the beta coefficient for the estimated price impact of objective quality increased as expert scores better reflected objective quality. These findings may suggest that if additional objective quality regressors with greater explanatory power for score were identified, then more precise estimates of the price impact of objective quality may result. In beta coefficient terms, the impact of objective quality may substantially exceed the price impact of subjective quality.

Finally, the study highlights the importance of the posited assumption for the relation between prices and objective and subjective quality. Even though various models are observationally equivalent, the posited specification has major implications for the interpretation of estimates. Imposing our preferred specification on the single-expert results of Cardebat, Figuet, and Paroissien (2014) possibly reverses their conclusion to suggest that subjective quality may dominate objective quality in explaining Bordeaux wine prices.

References

Ashenfelter, O. (2008). Predicting the quality and prices of Bordeaux wine. *Economic Journal*, 118(529), F174–F184.

Ashton, R.H. (2012). Reliability and consensus of experienced wine judges: Expertise within and between? *Journal of Wine Economics*, 7(1), 70–87.

Ashton, R.H. (2013). Is there consensus among wine quality ratings of prominent critics? An empirical analysis of red Bordeaux, 2004–2010. *Journal of Wine Economics*, 8(2), 225–234.

Bollen, K.A. (1989). *Structural Equations with Latent Variables*. New York: John Wiley and Sons.

Cardebat, J.-M., Figuet, J.-M., and Paroissien, E. (2014). Expert opinion and Bordeaux wine prices: An attempt to correct biases in subjective judgments. *Journal of Wine Economics*, 9 (3), 282–303.

Cardebat, J.-M., and Paroissien, E. (2015). Standardizing expert wine scores: An application for Bordeaux *en primeur*. *Journal of Wine Economics*, 10(3), 329–348.

Dubois, P., and Nauges, C. (2010). Identifying the effect of unobserved quality and expert reviews in the pricing of experience goods: Empirical application on Bordeaux wine. *International Journal of Industrial Organization*, 28(3), 205–212.

Ginsburgh, V., Monzak, M., and Monzak, A. (2013). Red wines of Médoc: What is wine tasting worth? *Journal of Wine Economics*, 8(2), 159–188.

Halliday, J. (2014). *Australian Wine Companion*, 2015 ed. Richmond Victoria, Australia: Hardie Grant Books.

Lecocq, S., and Visser, M. (2006). What determines wine prices: Objective vs. sensory characteristics. *Journal of Wine Economics*, 1(1), 42–56.

Masset, P., Weisskopf, J.-P., and Cossutta, M. (2015). Wine tasters, ratings and *en primeur* prices. *Journal of Wine Economics*, 10(1), 75–107.

McKenzie, C., and McAleer, M. (1997). On efficient estimation and correct inference in models with generated regressors: A general approach. *Japanese Economic Review*, 48 (4), 368–389.

Nelson, J.P., and Kennedy, P.E. (2009). The use (and abuse) of meta-analysis in environmental and natural resource economics: An assessment. *Environmental and Resource Economics*, 42(3), 345–377.

Oczkowski, E. (2001). Hedonic wine price functions and measurement error. *Economic Record*, 77(239), 374–382.

Oczkowski, E. (2016). The effect of weather on wine quality and prices: An Australian spatial analysis. *Journal of Wine Economics*, 11(1), 48–65.

Oczkowski, E., and Doucouliagos, H. (2015). Wine prices and quality ratings: A meta-regression analysis. *American Journal of Agricultural Economics*, 97(1), 103–121.

Reynolds, A.G., ed. (2010a). *Managing Wine Quality.* Vol. 1*, Viticulture and Wine Quality.* Oxford: Woodhead.

Reynolds, A.G., ed. (2010b). *Managing Wine Quality.* Vol. 2*, Oenology and Wine Quality.* Oxford: Woodhead.

Schamel, G., and Anderson, K. (2003). Wine quality and varietal, regional and winery reputations: Hedonic prices for Australia and New Zealand. *Economic Record*, 79(246), 357–369.

Stuen, E.T., Miller, J.R., and Stone, R.W. (2015). An analysis of wine critic consensus: A study of Washington and California wines. *Journal of Wine Economics*, 10(1), 47–61.

Wooldridge, J.M. (2006). *Introductory Econometrics: A Modern Approach*, 3rd ed. Mason, OH: Thomson/South-Western.