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SMES and black economic empowerment in South Africa

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Abstract

Black Economic Empowerment (BEE) is a South African policy that aims to decrease racial inequality and incentivises firms to train, hire, promote and transfer ownership to black people. However, the policy struggles to reach its goals. This article investigates the firm-level determinants of BEE compliance of small and medium-sized enterprises (SMEs) to understand the challenges towards BEE adoption for SMEs. Considering the BEE certification decision and the BEE compliance level, the results show that, e.g., firm location, age, industry, owner and manager characteristics, and firm size are significantly associated with BEE compliance.

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data provided are only for wines that have been evaluated by at least one expert. Along with the region of origin, vintage, alcohol level and type of wine (red, white, ros¶, fortified, sparkling) the database also includes the star ratings provided by consumer reviews, the number of reviews, the median price of transactions undertaken via the platform for each wine and the names of and scores given by experts. While they can be found on the website and have been analysed by others (see for example Kotonya et al, 2018), the data set provided to us does not contain verbal comments made by consumers. Nevertheless, there is sufficient information for the estimation of hedonic price equations, and the comparison of the relative importance of expert scores and consumer ratings in determining price differences in that framework. It should be noted that on the platform, while the price displayed is always the lowest price, there are often several sellers offer the same wine and prices may differ significantly. Promotional policies can also disrupt the establishment of a single price for a wine. It is important to stress that price variable provided in the data set and used in the hedonic price regressions is the median price of transactions made through Vivino and not the actual transaction price, a limitation that will be discussed further below. However, it should be noted that the aim of the study is not to explain precisely how the price is formed by the attributes of the wine, but to identify whether there are significant differences in the weighting of expert ratings and consumer ratings.

In order to be able to compare the effects of consumer ratings and expert scores, the former are mapped on to the same scale used by experts [50,100] using the procedure described in Bazen et al (2024). This is to avoid cardinality of the star rating system which would imply that a wine rated 4 stars is twice as good as a wine that is rated 2 stars. Further discussion of this issue can be found in Cardebat, Figuet and Paroissien (2014) and Oczkowski and Pawsey (2019).

2. Three research questions

Two hypotheses from earlier studies of Australian and French red wines will be tested for Italian and Spanish red wines:

1. Do consumer ratings have a bigger quantitative effect on wine prices than expert scores?

2. Do the effects of these two sources of information vary across the distribution of wine prices?

An additional hypothesis is tested:

3. Are the effects the same for white and red wines?

White wines tend to be less prestigious, less expensive[2] and have a shorter cellar life (see Chaudary and Siegel, 2016). It would be expected that expert scores are less important in determining their price compared to the case of red wine. This leaves an important potential role for consumer ratings.

[illegible]

3. The findings

3.1 Hedonic price regressions

Following Bazen et al (2024) we adopt two approaches to estimating hedonic price equations. Firstly, we estimate a linear regression to obtain an overall picture of the determinants of price differences. Secondly, we use quantile regression techniques in order to see whether the slope coefficients of the explanatory variables are the same at different points in the distribution of prices.

The baseline model consists of a regression of the logarithm of the wine price on the logarithms of the average consumer rating and the average expert score, dummy variables for each vintage and a set of dummy variables for geographical area (one for each the larger wine areas in terms of references on Vivino and for the region of production for smaller wine areas). This corresponds to the main specification used by Bazen et al (2024). This baseline specification is also estimated by quantile regression methods. In a second model we replace the geographical indicators by a full set of dummies for the specific wine areas called Protected Denominations of Origin or PDOs. There are over 400 in Italy and more than 100 in Spain. This additional specification therefore includes the most disaggregated information available on geographic area and is a useful robustness check. However it does so at the cost of over-fitting the model to the data, and in practice meant a quantile regression approach was not possible. As in the case of French red wines, there is not a high degree of concordance between the ratings made by consumers and the scores given by experts. For Italy the correlation coefficient is 0.25 for both types of wine, while for Spain the corresponding figure is 0.5. For French red wines, Bazen et al (2024) found a correlation of 0.4.

Table I

Italy	Red wines (2000-2019, n = 39,323)		White wines (2000-2019, n = 10,327)	
	Baseline	PDO dummies	Baseline	PDO dummies
Consumer rating (France: 9.41)	7.26 (0.07)	6.89 (0.07)	5.02 (0.12)	4.67 (0.12)
Expert score (France: 5.60)	3.65 (0.08)	3.49 (0.08)	2.64 (0.15)	2.62 (0.15)
RД	0.57	0.60	0.34	0.39
Number of parameters	54	321	44	235

Estimated standard errors in parentheses. The baseline model includes dummy variables for the vintage, the main wine areas and the region for wine areas with few referenced wines. The second model includes a full set of dummy variables, one for each wine area however small, along with dummies for the vintage.

(a) Italy

The quantitative effect of consumer ratings on red wine prices is bigger than that of expert scores ¯ see Table I. This confirms the finding for French red wines. The elasticity estimates are smaller than in the French case (7.3 compared to 9.4). Using the full set of PDO dummies changes slightly the size of these effects but not their relative importance. The quantitative importance of consumer and expert evaluations is smaller for Italian white wines (40% smaller) but consumer ratings are still quantitatively more important than expert scores. The inclusion of the PDO dummies instead of regional variables does not significantly change the estimated elasticities.

Table II

Spain	Red wines (2000-2019, n = 12,406)		White wines (2006-2019, n = 2,828)	
	Baseline	PDO dummies	Baseline	PDO dummies
Consumer rating	13.27 (0.17)	13.31 (0.18)	7.44 (0.29)	7.36 (0.29)
Expert score	6.15 (0.16)	6.01 (0.17)	4.31 (0.30)	4.16 (0.31)
RД	0.62	0.63	0.45	0.48
Number of parameters	41	112	39	100

Estimated standard errors in parentheses. The baseline model includes dummy variables for the vintage, the main wine areas and the region for wine areas with few referenced wines. The second model includes a full set of dummy variables, one for each wine area however small, along with dummies for the vintage.

(b) Spain

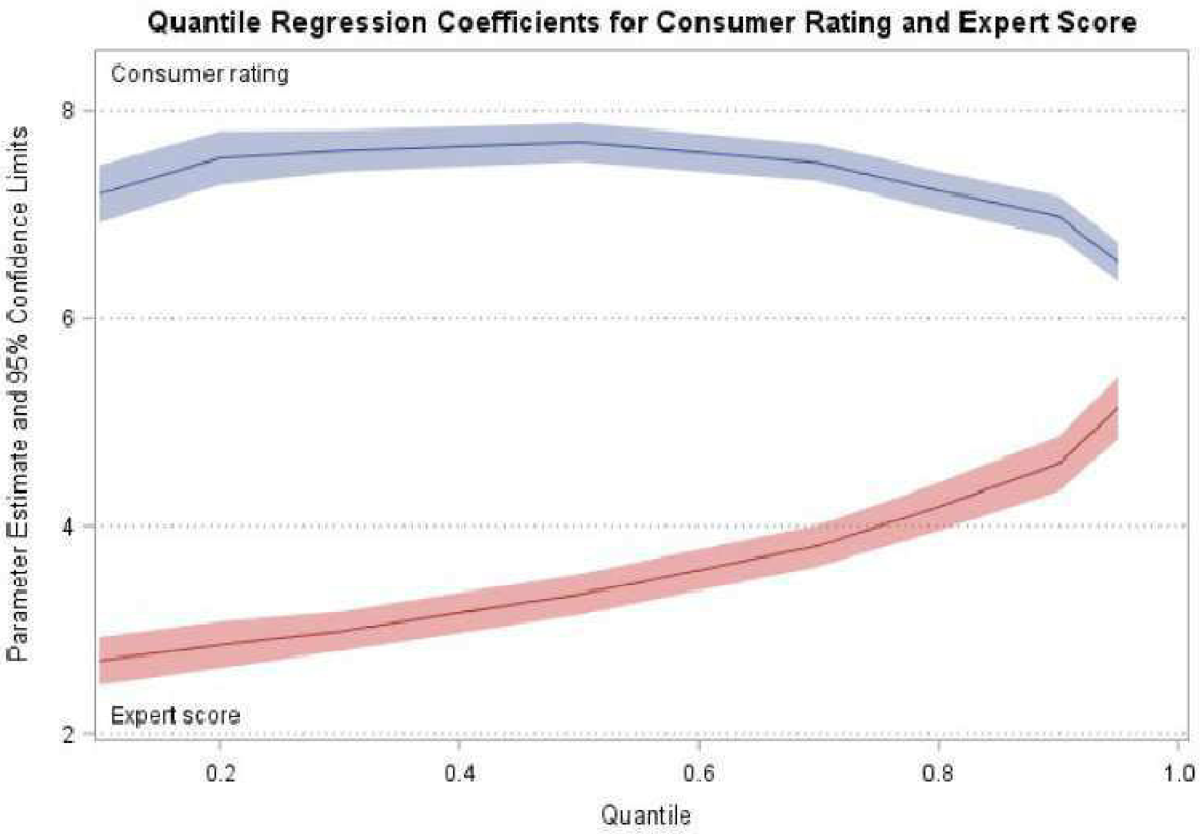
The elasticity estimates for Spanish wines (red and white) are much larger than those for Italy - see Table II. The consumer rating elasticity for red wine is over 13 compared to 9.4 for France and 7.3 for Italy. The elasticity for expert scores is half that of consumer ratings. Consumer ratings have a larger quantitative impact on red wine prices than expert scores. The estimates do not change when a full set of PDO dummies is used in the place of geographical area.

3.2 Quantile regression estimates

Due to the large number of parameters to be estimated in the model with the full set of PDO dummies, we only use the baseline specification to analyse the heterogeneity of the elasticity estimates across the distribution of prices. If the quantile elasticity estimates are constant across the distribution, then the quantile regressions will be a series of parallel lines and convey no more information than the linear regression estimates.

For French red wines, Bazen et al (2024) find that while the consumer ratings coefficient is always bigger than that of expert scores, the gap between the two narrows monotonically as we move up the upper half of the distribution. This is due to a higher elasticity for expert scores for higher priced wines, rather than a smaller one for consumer ratings.

Figure 1 Italian red wines



The same overall conclusions are found for Italian red wines: dominance of the consumer ratings effect but with a narrowing of the gap between the two elasticities in the upper quantiles (Figure 1). For Spanish red wines, there is a substantial difference between the estimates ‾ the consumer ratings elasticity being more than twice the expert score elasticity across the distribution except in the highest decile where there is a slight narrowing (Figure 2).

For Italian white wines, the picture is similar to that of red wines (Figure 3). There exists a substantial gap between the consumer ratings and expert scores elasticity in the lower half of the price distribution (the former 2.5 times the latter). However, the gap narrows as we move up the distribution due to a higher estimated expert scores elasticity. In the top 10% of the distribution the gap is just about statistically significant.

Figure 2 Spanish red wines

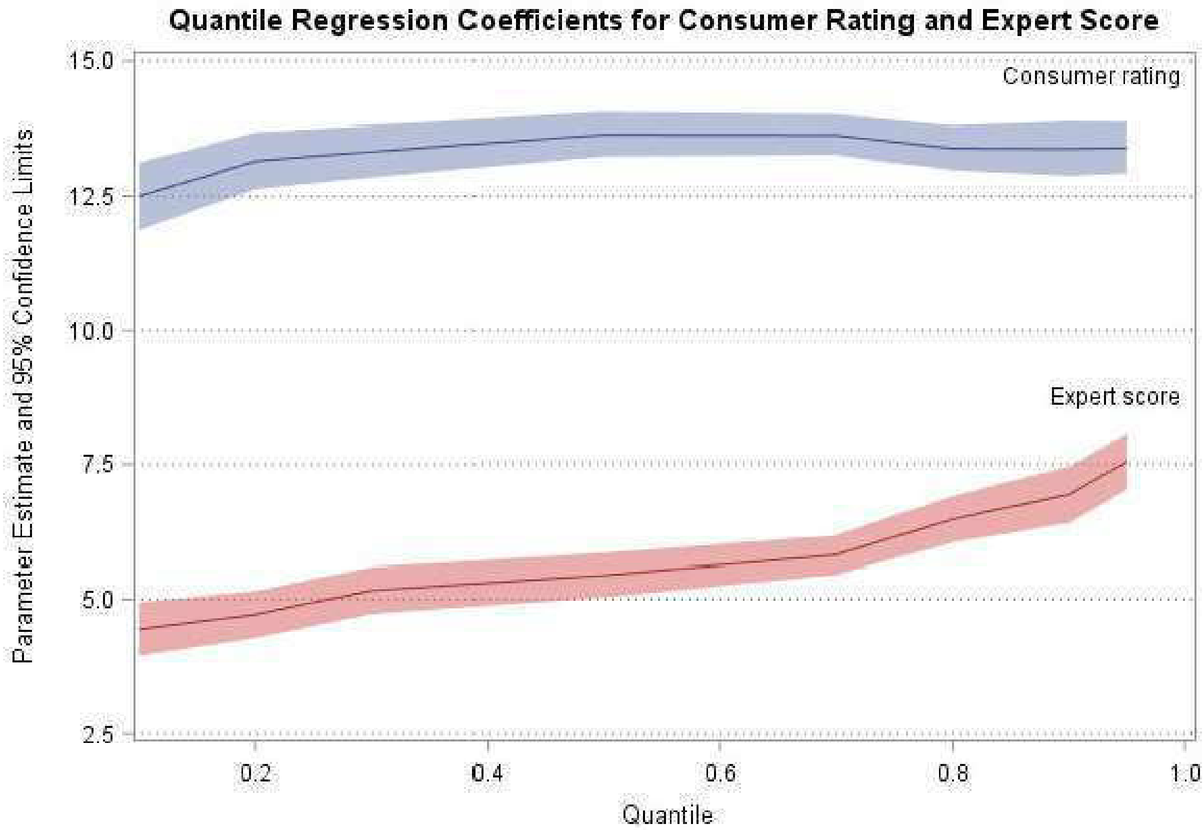


Figure 3 Italian white wines

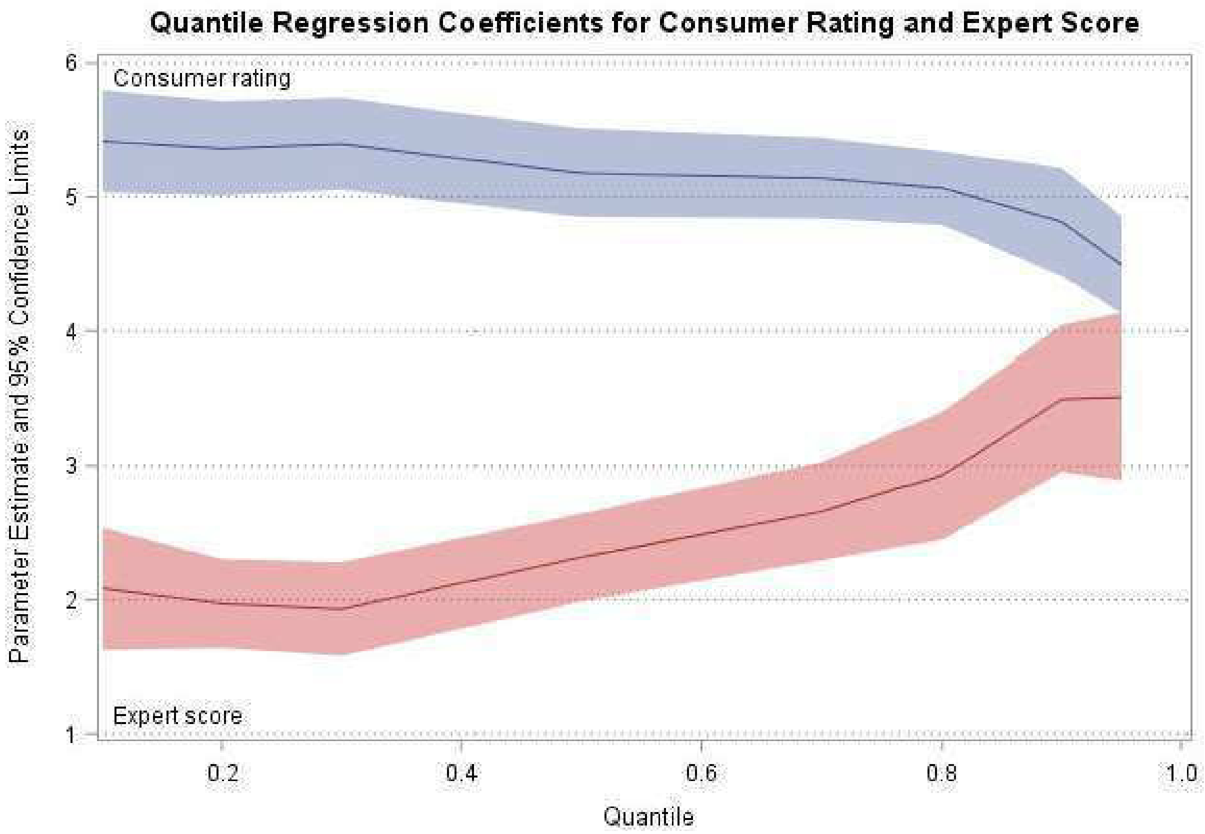
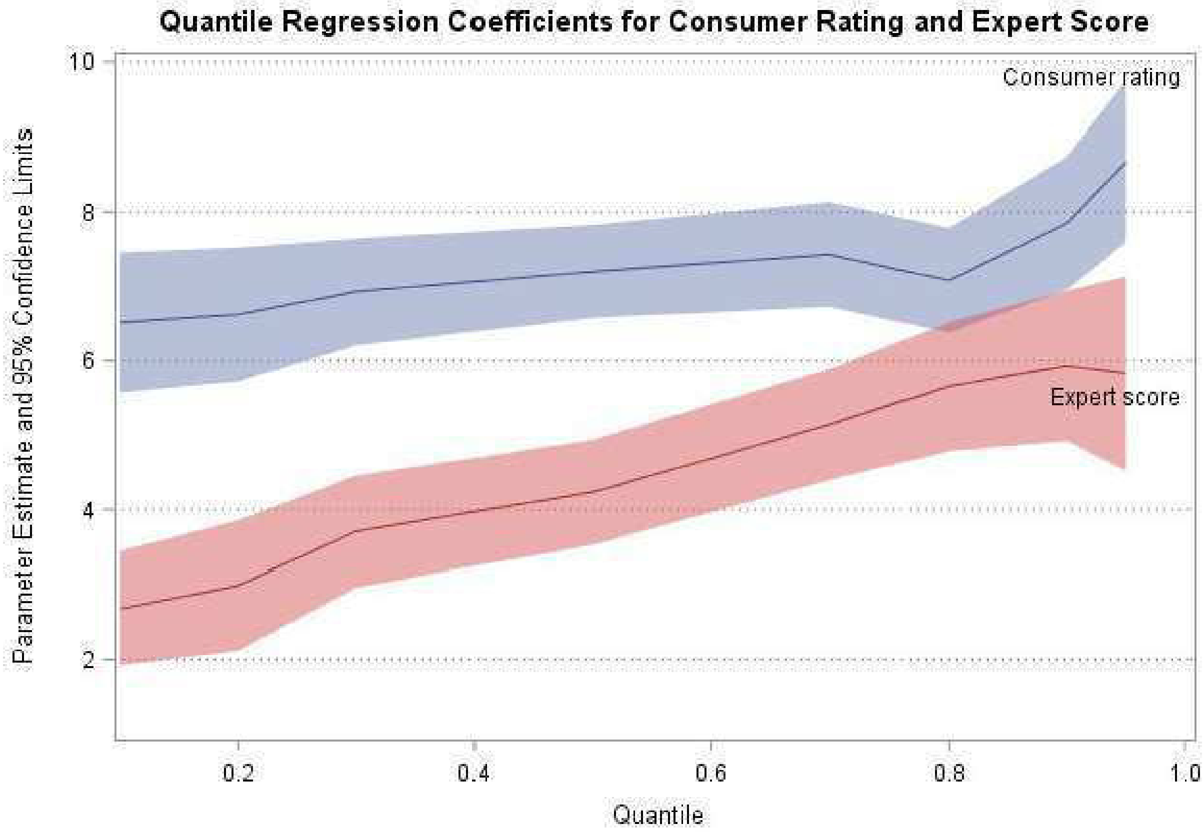


Figure 4 Spanish white wines



For Spanish white wines the tendency is even more pronounced (Figure 4). The effect of consumer ratings dominates up to the 80th percentile, but the gap between the two elasticities progressively narrows as we move up the price distribution. In the upper decile, the two effects are not significantly different.

4. Discussion

4.1 White v Red wines

The effect of expert scores on white wine prices is significantly smaller than for red wines from both Italy and Spain. However, the same is true for the effect of consumer ratings especially for Spanish white wines, and to a lesser extent Italian whites. The consumer effect is still the more dominant by far. Compared to red wines, the results for white wines confirm two points. Firstly, that the peer effect is significantly greater than the expert effect. The results for white wine are qualitatively similar to those for red wine. Secondly, score-related information is less valued for white wines than for reds supporting the notion that white wines are perceived as being less prestigious. This last result is interesting because it is independent of wine price. Quantile regressions show that scores have a smaller impact on the price of white wines compared to reds, even when the price of white wines is higher than that of reds (the coefficients for the last quantiles of white wines are lower than those for the first quantiles of red wines). The value of information depends more on the colour of the wine than its price.

This would confirm the existence of a cognitive bias in consumer behaviour, probably of cultural origin (Parr, 2019), which influences consumers' risk perception. Such a bias has already been in expert evaluations (Cardebat and Livat, 2016). This bias means that consumers take less account of information (which is of limited value) on white wines. They probably feel less at risk when choosing a white wine. White wine would thus be experienced as less complex. It would carry less uncertainty. At this stage, these assertions are purely hypothetical, but this paper opens up an interesting avenue for research on consumer appreciation of white wine. It is worth remembering that white wine consumption has been constantly rising, and has now overtaken that of red wine (see OIV, 2023). This lesser complexity experienced by the consumer could be one of the causes of this crossover in consumption trends in red and white wines.

4.2 The role of consumer ratings

Unlike expert scores which tend to be published at the time a wine is first commercialised, average consumer ratings are built up over a period of time. However, once the first ratings are made and the average is initially established, typically it does not vary much thereafter (Gokcekus and Nottebaum (2011) provide an interesting analysis of how consumer ratings are formed for a sample of American wines). This can give a prominent role for ːfirst-movers˘ who then emerge as ːinfluencers˘ (this is emphasised by Kotonya et al, 2018). Even if a subsequent consumer gives a one or two star rating, the average score for a wine will hardly change. When interpreting the coefficient on the consumer rating variable it is therefore necessary to use a counterfactual interpretation rather a time-varying one. For two wines which are in every respect identical in terms of the other explanatory variables but one has an average rating from consumers that is 1% higher, then its price is predicted to be higher by the value of the elasticity in percentage terms.

A second issue is that the kind of consumer buying sometimes very expensive wines and rating them on the Vivino website, tends to be more knowledgeable than the average wine consumer. In the past they would have been called ːwine buffs˘ and in more modern language, ːwine geeks˘. For these people, wine is a hobby and not just a consumer good. The ubiquitous nature of the internet and costless access to their evaluations, means that some of them emerge as influencers who are affecting potential consumers˘ decisions and (unintentionally) competing with experts in the provision of information about wines.

5. Some limitations

While the data set obtained contains over 145,000 references, it is in fact only a subset of the wines listed on Vivino for the countries studied. The aim of the research project was to compare expert scores and consumer ratings as determinants of price differences, and so only wines which have at least one expert evaluation are included. Consumer ratings will certainly have an effect on the prices of other wines which experts have not considered. In that sense the results here should be viewed in terms of the relative effect of consumer and expert evaluations.

A second limitation which is present in any hedonic price analysis of wine is that the price of a given wine is not unique. It depends where it is purchased ¯ winery, supermarket, restaurant ¯ and mark-ups will vary. In the data set provided the variable is the median price for transactions made via the platform and so this heterogeneity is therefore ignored. Hedonic analyses in wine price research typically suffer from this limitation. Even when actual transaction prices are used, significant disparities may exist in the price of the same wine sold in the same area and at the same date, as the law of one price is not present in the market for wine (see Ashenfelter, 1989; Cardebat et al., 2017). The limitation of the quality of price data is therefore clear, but it is inherent in all studies in this field.

Thirdly, an issue which is common to cross section data sets which contain time-varying variables (such as durations) is that the snapshot observed is the outcome of cumulative processes. The ideal form of data to analyse how consumer ratings shape wine prices would be one that follows :cohorts˘ of wines from the moment they come onto the market and registers how their prices evolve in relation to the consumer evaluations posted on the website over time. While the cross section hedonic price analysis controls for vintage, it will not capture how changes in consumers˘ratings lead to price variations.

Fourthly, using average scores (from users and experts) can hide information. Depending on who is rating, the buyer may be more or less influenced in the price they are willing to pay. To take a simple example, an excellent rating given by Robert Parker has an influence on price that goes well beyond an average rating given by a panel of experts (Masset et al, 2015). This problem of aggregation in the wine world has been highlighted by several authors (see, for example, Cao and Stokes, 2017; Kwong and Sun, 2018). However, it mainly concerns the most sought-after, fine wines. Furthermore, user ratings do not benefit from image effects such as the `Parker effect,_ even if users are known by their pseudonyms and can create communities. Information on the names users must be sought specifically, and only average ratings appear directly on the website. They were not included in the data set provided. This limitation on the aggregation effect is unlikely to invalidate the analysis based on an average rating.

A final point that has already been addressed by Oczkowski and Pawsey (2019) and Bazen et al (2024) is the possibility that price is a factor that affects consumer ratings (eg good value for money), giving rise to a form of reverse causality. The papers cited use an instrumental variables approach to explore this possibility, but neither finds evidence of bias as a result of price being such a factor. Other evidence using Vivino data in Kotonya et al (2018) confirms the finding that prices are not really relevant for consumer evaluations of wines. The absence of such an effect may be because when a consumer makes a purchase, the decision on what price to pay has been determined by the context in which it is to be consumed (for example a special occasion or gift). After all, the prices in the samples used here are not negligible (the median prices run from 15 to 28 euros a bottle).

6. Conclusions

The findings in this paper for Italy and Spain confirm the findings for France, namely that consumer ratings are quantitatively more important than expert scores in the determination of wine prices. The information provided on the Vivino platform and the average star rating provide prospective consumers with information about the quality of wine over and above what can be gleaned from the label. This source is also an alternative to the information provided by experts, whose role is apparently less important quantitatively than peer ratings.

From a marketing perspective, the Vivino consumer rating could be used along with expert scores and wine prizes as an additional selling point. In the context of the market for information, our findings suggest the emergence of peer ratings may be occurring at the expense of experts˘ evaluations. This result is line with the emerging literature on the joint role of peers and experts in the hospitality sector (Keh and Sun, 2018; Yoo and Suh, 2022).

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APPENDIX

Table A.1. Descriptive statistics				
	Mean	Median	Minimum	Maximum
Italian Red ([illegible])				
Expert score	88.3	88.0	57	100
Consumer rating	3.95	3.96	2.34	5
Price in euros	43.10	27.20	3.11	934.16
Spanish Red ([illegible])				
Expert score	90.4	90	74	100
Consumer rating	3.91	3.91	2.30	4.88
Price in euros	35.14	21.07	3.01	995
Italian White ([illegible])				
Expert score	88.05	88.0	71	100
Consumer rating	3.74	3.75	2.41	4.80
Price in euros	19.60	15.34	3.00	521.90
Spanish White ([illegible])				
Expert score	90.15	90	76	100
Consumer rating	3.83	3.83	2.6	4.68
Price in euros	21.13	16.87	3.04	333.30

Source: Vivino.com