

## The Roles of Social Media and Expert Reviews in the Market for High-End Goods: A Case Study Using Wine

*Collaborators: Peter Pedroni (Williams College) & Stephen Sheppard (Williams College)*

### Project Note

This project expands on work I presented at the Annual AAWE Conference in 2016. Since then, I have been rebuilding our unique time series panel dataset from the ground up in order to significantly improve: (1) the quality and scope of the dataset and (2) the replicability and transparency of the data collection process. (See Section 2 for details on the updated data collection steps.) I am currently in the final steps of data collection and plan to generate novel empirical results in the coming months. With the support of the AAWE Wine Economics Research Scholarship, I would work with my collaborators to generate a cohesive working paper for eventual publication and presentation this summer.

### 1 Project Introduction

The impact of expert reviews on market price has been a perennial favorite subject of study for wine and other high-end consumer goods. With such studies, there is often a temptation to attribute the impact of an expert review entirely to the reputation of the reviewer. Depending on one's view of the nature of expert reviews, this can lead to the impression that market price in the world of wine and other so-called luxury goods is highly influenced by the proclamations of a handful of expert reviewers. By contrast, in this project, we argue that the information from expert reviews constitutes a component of a broader signal extraction problem undertaken by consumers of such goods, and that it is important not to conflate the quality signal component of the expert reviewer with the purely reputational effect – the publicity effect – of the reviewer, which is independent of the quality signal.

To empirically evaluate this signal extraction problem, we take advantage of the unique nature of the market for high-end wines. For one, the market represents a leading example of the phenomenon of potentially large influences from expert reviews. Moreover, the recent growth of the social media forum CellarTracker.com provides an interesting opportunity to track a dimension of the consumer evaluation of wines that can be used to help inform and interpret market data on price movements. To this end, we have constructed a unique time series panel of amateur wine reviews obtained from CellarTracker, which we pair with similarly dimensioned panels of auction prices for the corresponding wines. We collaborated with Peter Gibson of *Wine Market Journal* and Eric LeVine of CellarTracker to generate a unique dataset of 1990-2010 vintage wines that are rich in both auction price and amateur review data. Once we collect the necessary wine critic data, we will be able to exploit the unique nature of our constructed dataset by using structural vector autoregression (VAR), as developed by Pedroni (2013), to disentangle a review's quality signal from its publicity effect. As such, the project brings together expert reviews, social media data, and auction prices in order to empirically investigate the roles of social media and experts in high-end good markets.

## 2 Data Collection

### 2.1 Completed Steps

Our model of signal extraction applies specifically to high-end goods. As such, we narrowed our data collection to high-end wines, which we defined as those that are rich in auction data. We then worked with Peter Gibson, Editor of the *Wine Market Journal*, to identify such wines. With his unique institutional access to more than 1.3 million auction prices over 50 thousand wines, we were able to query all vintage 1990-2010 wines with at least 20 quarters of consecutive auction data in some period from 2004 to present.<sup>1</sup> This query of the *Wine Market Journal* data resulted in 30,258 quarters of price data on 873 wines.

The next dimension of data required for the analysis was amateur reviews. The natural source for this data was CellarTracker.com, which boasts millions of tasting notes written by users. We requested data on wines from regions that had at least 20 wines in the 873 sample. In effect, the requested high-end wine sample consisted of 838 wines from the following regions: Bordeaux, California, Burgundy, Rhone, Champagne, and Italy (Piedmont and Tuscany).<sup>2</sup> We then worked with Eric LeVine to acquire all CellarTracker tasting note data on those 838 wines. In the end, we collected 113,583 CellarTracker tasting notes, yielding 27,386 quarterly average CellarTracker scores across the 838 wines.<sup>3</sup>

After merging the quarterly average data from two sources (*Wine Market Journal* and CellarTracker), there are a resulting 20,370 quarters that possess both auction and CellarTracker quarterly average values over the 838 wines. Therefore, the current dataset is 20,370 observations that feature both quarterly average auction and amateur review scores of 838 high-end wines from Bordeaux, California, Burgundy, Rhone, Champagne, and Italy (Piedmont and Tuscany).

### 2.2 Future Steps

Intuitively, the next step in dataset creation is to find the subset of high-end wines that are also consistently scored on CellarTracker. To fit econometric requirements, we must require a minimum number of consecutive quarters of both amateur reviews and auction data to form our unbalanced panel times series of wines. For the purposes of rigor, we also need to set some minimum number of CellarTracker reviews per quarter.<sup>4</sup> One possible set of restrictions that I have tested is: a minimum of 3 CellarTracker reviews per quarter and a minimum of 16 consecutive quarters of online review and auction data. These restrictions yield a subset of 122 high-end wines from the previous 838.

Given this subset of 122, the next step is to collect expert review scores. The expert reviewers for the regions in our sample are: Robert Parker, Allen Meadows, Jeb Dunnuck, Peter Liem, and Stephen Tanzer. We plan to subscribe to their relevant websites and sync them (all non-Parker ones) up to CellarTracker.<sup>5</sup> In other words, we can simplify the search

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<sup>1</sup>We want the consecutive 20+ quarters to be recent (2004 or after) so that there will be possible overlap with CellarTracker data. (CellarTracker was publicly launched in 2004.)

<sup>2</sup>In other words, these are the regions that had at least 20 wines in the first cut of the data acquired from *Wine Market Journal*.

<sup>3</sup>CellarTracker tasting notes have a numerical as well as a textual component. 98,023 of the 113,583 ratings have a numerical component.

<sup>4</sup>One person's review should not form the entire basis of a CellarTracker quarterly average.

<sup>5</sup>All experts except for Robert Parker allow their reviews to be displayed to their subscribers in the

for Meadows, Dunnuck, Liem, and Tanzer reviews via consolidating their reviews into one platform (CellarTracker). Meanwhile, we will search for Parker reviews directly through his website. The addition of these expert review scores into the relevant quarters of the 122 wine dataset would complete the proposed data collection process.<sup>6</sup>

### 3 Signal Extraction Intuition

My collaborators and I plan to use our final dataset in conjunction with the recently developed panel structural vector autoregressive methods of Pedroni (2013) to decompose the signal contained in expert reviews into their component parts. To give some further background on our modeling approach and how we accomplish the decomposition of expert reviews into component parts, it is worth elaborating on how we view the signal extraction problem and how it relates to the interaction between professional and amateur social media-based reviews. In particular, we consider that when evaluating a product's quality, consumers make use of a blend of their own evaluations and those of expert reviewers. When a high-end product has attributes that are not homogeneous, and that are difficult to know prior to its consumption, expert reviews can have a potentially large impact on the individual consumer's evaluation of quality.

Furthermore, it is worth noting that high-end wines do not merely represent leading examples of this phenomenon, they also present rich and interesting signal extraction problems. In contrast to some luxury goods, the quality of a given bottle of wine is not fixed, but rather evolves over time. Moreover, the quality does not simply depreciate or appreciate over time, but rather tends to be non-monotonic, rising for a period before falling. Expert reviewers render opinions on quality not simply as a static notion, but in large part as a forecast of how the wine is expected to evolve.

Confounding the signal extraction problem is the fact that it is not altogether clear what expert reviewers intend as the comparison benchmark. Clearly a higher rating on a wine is not intended to convey that the wine is superior in quality to a lesser rated wine in some absolute sense, since the rating is presumably conditional on a number of unknown factors, including perhaps the category of wine, the vintage, the price of the wine, or perhaps even the reviewer's prior expectation of the specific bottling of wine. The expert reviews, in turn, impact the consumer's evaluation of the quality of wine as part of the signal extraction, and both, in turn, impact the evolution of market price. In short, the relationship between quality, evaluation of quality and price are intertwined in a dynamic and complex manner.

### 4 Econometric Methodology

The aforementioned aspect of complex, unknown, interdependent dynamics falls squarely in the realm of what structural vector autoregression (VAR) analysis is intended to address in the time series literature. However, the fruitful interpretation of VAR analysis typically requires structure. For this, some of the special aspects of social media reviews for wine offer attractive features that can be exploited for the purposes of structural analysis. For instance, in contrast to other products that are reviewed via social media, wine, once released, is exogenous in its quality evolution with respect to reviews. Whereas a restaurant might

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CellarTracker interface.

<sup>6</sup>It is likely that some of the 122 wines would be eliminated from the sample due to a lack of expert reviews in the intervals necessary for application of our econometric approach.

adjust its quality in response to social media reviews, wine, once produced and released, does not.

In particular, the social media CellarTracker consists of hundreds of thousands of users, who are predominantly highly informed wine consumers, who have written about 6 million tasting notes. The network's popularity within the wine community makes it a natural choice for empirically tracking the opinions of informed wine consumers. Furthermore, for high-end wines, the number of amateur reviews can be fairly large, and therefore difficult to manipulate by any one reviewer. The complete review history of each reviewer is easily available on CellarTracker. In principle, this allows one to easily discount reviews that were posted by individuals who have posted only a small number of anomalous reviews.<sup>7</sup>

In this context, structural VAR analysis can aid in more nuanced decomposition of the quality signal from expert reviews and their impact on the market. However, in order to exploit the time series information from a panel of high-end wines, one must recognize that the complex, unknown interdependent dynamics are likely to vary considerably among the wines. Simply pooling the dynamics as if they were identical across wines leads to a well-known problem of inconsistent estimation and inference, and is not an option. Furthermore, the vintage effects create commonalities among the wines of the same vintage, which must be accommodated for valid inference. The panel structural VAR method developed in Pedroni (2013) has been designed specifically to address such issues, which typically arise in time series panels, and it is on the basis of this methodology that we exploit the information in our data set.

## 5 Previous results

The preliminary results using our old dataset appear promising, and point to the likelihood that expert reviews influence the market primarily due to the publicity effect that accompanies such reviews rather than due to their quality signal. Specifically, price responds weakly to the quality component that we derive from expert reviews, but strongly to the remaining reputational component. Moreover, we also find that, in the case of some wines, CellarTracker quantitative ratings can decrease in response to favorable Parker reviews.<sup>8</sup> In these cases, there seems to be a negative effect from the reputational component part of the Parker review that can outweigh the positive effect of the favorable potential underlying quality signal. This result has the potential to further our understanding of how consumers rate conditional on both price and quality expectations in the arena of high-end goods.

## 6 Building new results

Since we are rebuilding the times series panel dataset, we will be generating new results again using the panel structural VAR method. The robustness of the current data collection procedure allows us to use a much more thorough and complete set of auction and CellarTracker data points in the proposed analysis. Given CellarTracker's growth in recent years, updating the dataset to cover tasting notes through mid-2017 is a major improvement over the previous dataset, which covered tasting notes only through 2013.

Moreover, the updated dataset will boast a number of new features that benefit the

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<sup>7</sup>Although in practice, at least anecdotally, this type of manipulation does not appear to occur much.

<sup>8</sup>The old dataset only included Parker review scores, so these conclusions were limited to his reviews. This will change in the future analysis.

project's scope and relevance. For one, the new dataset is not limited to wines from the regions of California and Bordeaux, as was the case with the previous dataset. Furthermore, the data will also include wine scores from multiple expert reviewers. The previous dataset only covered reviews by Robert Parker. The new dataset's additional inclusion of Allen Meadows, Jeb Dunnuck, Peter Liem, and Stephen Tanzer would allow us to compare the differential publicity and quality signals across reviewers. It is possible that not all reviewers generate the same signal to consumers.

Lastly, preliminary results, as presented at the Annual AAWE Conference in 2016, highlighted heterogeneity of CellarTracker scores across different wines, especially across geographic lines (namely, California vs. Bordeaux). There was significant interest in investigating this heterogeneity using the text that accompanies CellarTracker reviews, however, we did not have access to such data. Given the structure of the new dataset, those textual components are now accessible. In effect, descriptive characteristics of wines can be investigated through text analysis to explore the context for any such heterogeneity. This opens up a new dimension of data to investigate.

## 7 Contribution to the literature

The data and methods in this project provide a unique opportunity to evaluate the roles of expert reviews and social media in the market for high-end goods. The project joins a vast literature covering quality perception, reputation, prices, and other foundational issues in the sphere of microeconomics. In particular, the research contributes to a growing field of economics that uses online data in order to better understand the concept of quality, which previously has been restricted primarily to the realm of theoretical microeconomic papers. This work also addresses concepts popularized by modern sociological and computer science research such as herd behavior and the general problem of preference construction when other consumers' preferences as well as those of experts are visible to the individual.

## 8 Conclusion

This proposed project significantly expands on work I presented at the Annual AAWE Conference in 2016. My collaborators and I have already completed many of the steps in building an improved times series panel dataset with the help of the *Wine Market Journal* and CellarTracker. The AAWE Wine Economics Research Scholarship would support a number of steps in this ongoing project: (1) finishing the last phase of data collection (expert review data collection), (2) building out the theory section based on the signal extraction problem, and (3) generating new results using the panel SVAR methodology. In short, the AAWE Wine Economics Research Scholarship would provide me with the resources to develop the project into a concrete working paper to share and discuss with the wine economics community.

## References

- [1] Pedroni, P. (2013) Structural Panel VARs, *Econometrics*, 1 (2), 180-206.