Uncorking Expert Reviews with Social Media: A Case Study Served with Wine

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High-end Goods and Experts

“For that price I’d want it to love me in return.”  “Our best – rated over 700 in both Math and Verbal”
A Different Type of Reviewer

Online mechanisms for recording and transmitting amateur reviews

1. Carriage House Cafe
   - 290 reviews
   - $ - Sandwiches, Breakfast & Brunch, American (New)
   - been here 4 times now. Something for everyone, with a nice mix of breakfast and lunch, although it seems like they’ve shifted to more simple breakfast foods when they went their... read more

2. Coal Yard Cafe
   - 43 reviews
   - $ - Bagels, Coffee & Tea, Sandwiches
   - Good for Lunch
   - Let’s say you’re visiting prestigious Cornell University and have a hankering for some sensational eggs at breakfast, or the perfect sandwich at lunch. Incredibly specific, I know.... read more

3. Gorges Subs
   - 115 reviews
   - $ - Salad, Soup, Sandwiches
   - Good for Lunch
   - be my last meal. The panda wings are simply amazing. And nine dollars for a sub? My ever empty wallet weeps with joy. Nine dollars for a foot long sub overflowing with delicious... read more

4. Ithaca Bakery
   - 239 reviews
   - $ - Delis, Breakfast & Brunch, Bakeries
   - Good for Lunch
   - This place is more than just a bakery. It’s coffee, breakfast, lunch, and dinner. We found plenty of veggie options for us and it’s kid friendly! Our daughter was able to play with a... read more
High-end Crowd Wisdom

Similar mechanisms for sharing information on high-end goods

1990 Château Angélus
RED BORDEAUX BLEND

France > Bordeaux > Libournais > St. Émilion Grand Cru
Auction price: Register or sign-in to see quarterly averages or visit the Wine Market Journal
Drink between: 2002 - 2019 (Add My Dates)

4/30/2018 - ENGLISHMAN'S CLARET WROTE:
Angelus Dinner: The second bottle from the same case, this shows a totally different profile. Here it's the merlot that's emphasized and what a rich, sumptuous nose it shows. Raspberry, plum, ganache, Perigord truffle, cedar. Loads of swagger without losing any poise - this walks a fine line between hedonism and elegance. Round palate. Long finish. Just a delight - here's the real 1990 Angelus! 95-96

Albright et al. (AAWE 2018) Uncorking Expert Reviews with Social Media
Exploiting simultaneous existence of amateurs & experts

Use social media (amateur) reviews to untangle two components that are combined in expert reviews: the quality of the product under review and the reputation of the reviewer.
Why Serve a Case Study with Wine?

- Potentially large influences from expert reviews
- Once produced and released, evolution of wine quality is exogenous to reviews (unlike the case with, say, restaurants)
- CellarTracker.com consists of half a million users as well as over 7 million tasting notes
- Ashenfelter and Jones (2013) on the demand for expert information:
  - Could be due to private information or...
  - Expert ratings may “create values that are indendent of the function”
Generated a dataset of 355 1990-2010 vintage wines that are rich in both auction price and social media review data (2004Q1-2017Q2)

Collected expert reviews on the sample:
- 240 from Robert Parker’s RobertParker.com
- 399 from Jancis Robinson’s JancisRobinson.com
- 146 from Antonio Galloni’s Vinous.com

Despite no regional restrictions, sample dominated by wines from Bordeaux (175) and California (109)
Picturing the Data

Time Series of Mean Real Auction Prices

Time Series of Mean CellarTracker Scores

via Albright et al. (2018)
Empirical Motivation

Diff-in-diff specification to investigate reduced-form effects of “high” expert reviews:

\[ \log A_{it} = \beta_1 H_{it} + \alpha_i + \delta_t + \epsilon_{it} \]

- \( A_{it} \) real quarterly average auction price for wine \( i \) in quarter \( t \)
- \( H_{it} \) is an indicator for if wine \( i \) had a high expert review affiliated with it at quarter \( t \)
  - “High” reviews = above median scores – above 95, 17.5, and 95 for Parker, Robinson, and Vinous, respectively
- \( \alpha_i \) are wine specific fixed effects and \( \delta_t \) are quarter fixed effects
- Control for wine-specific linear trends as a robustness check
Controlling for wine-specific linear trends only Parker effects survive → a high Parker score is affiliated with a 9.6% increase in auction price
Scores associated with price movement

But, reviewer scores are presumably correlated with quality

- Are impacts because the reviewer score movements are proxying for information on quality that is being released?
- Or, because they are reflecting the pure reputational or publicity effects of the expert?
- Both?

How can we investigate the mechanism behind reduced-form effects?

- Exploit simultaneous existence of experts and amateur reviews
- Use Pedroni (2013) panel SVAR approach; requires restriction for identification
Expert reviews depend on taste-testing for quality and some perceived standard (established reputation of wine producer, other factors outside the bottle represented by $\tau$)

$$\varrho(q, \tau) = p_0 + p_1 q + p_2 \tau + \epsilon_{\rho}$$

Amateurs reviews ($\gamma$) are based on tasting and their expectations, as derived from prices ($p$)

$$\gamma(p, q) = k_0 + k_1 p + k_2 q + \epsilon_{\gamma}$$

This paired with signal extraction argument yields: $\gamma_t$ depends on lagged $\tau$, not current $\tau$
Translate model intuition to panel structural VAR restriction (Pedroni 2013)

- “Quality information shocks” = $\epsilon_{it}^\rho$
  - Think shock associated with $q$ from model
- “Other shocks” = $\epsilon_{it}^\kappa$
  - Think shock associated with $\tau$ from model

Resulting identification strategy: no immediate impact effect from $\epsilon_{it}^\kappa$ to the average CellarTracker score in the period of the shock
Empirical Strategy: Panel SVAR Approach

Data: $\Delta z_{it}$ $2 \times 1$ vector of panel time series variables observed over time periods $t = 1, \ldots, T_i$ for units $i = 1, \ldots, N_t$

- $\Delta z_{1,it} =$ CellarTracker review score average for wine $i$ at time $t$
- $\Delta z_{2,it} =$ natural log of the auction price average for wine $i$ at time $t$

Want: responses to our shocks of interest, $\epsilon_{it} = (\epsilon_{it}^\rho, \epsilon_{it}^\kappa)'$

Need: Mapping from reduced form VAR to structural form

- Use identification strategy!
  - Mathematically, set element of $2 \times 2$ short run impact matrix restriction corresponding to response of CellarTracker to “other” shocks to be 0
Treat expert reviews as events with known timing, but unknown consequences

- Analogous to event analysis in time series analysis

Events entered into the VAR estimation for each wine as dummies $d_{it}$

- Takes the value 0 up to the point of the event
- Takes on the value of event (defined as change in expert score) from the point in time at which it occurs onward through the remainder of the sample
Mapping from reduced to structural with $d_{it}$ → decomposition of the event effects into components that are analogous to $\epsilon^\rho_{it}$ and $\epsilon^\kappa_{it}$

- Expert reviews (1) are an innovation to the quality information stockpile (quality information shock)
- Expert reviews (2) disseminate information to a larger audience (due to his reputation), thus raising awareness (publicity shock)
Results

- Present reaction of endogenous variable log auction price at time of shocks and during subsequent time periods
- Different response for each wine; depict interquartile range (25th, median, 75th) and mean of responses to one unit increase in expert review
- Illustrate for Parker, Robinson, and Vinous subsamples
Results: Responses to Experts

Log Auction Price Impulse Responses to Expert Shocks

We present the interquartile ranges of responses over 6 quarters. The thick black lines are medians and the red points are means. (Albright et al. 2018)
Results: Decomposed Responses to Experts

Log Auction Price Impulse Responses to Quality Information Expert Shocks

Log Auction Price Impulse Responses to Other Expert Shocks

We present the interquartile ranges of responses over 6 quarters. The thick black lines are medians and the red points are means. (Albright et al. 2018)
Results Summary

- Parker moves auction price more than his competition – a one unit increase in his scores means an average 0.2% increase in auction prices.
- Magnitudes of the reviewer effects in all three above are much smaller than in the differences-in-differences results; here we use a unit change reviews, rather than an indicator for “high” versus “low” score.
- Quality information/other channels are differentially important by reviewer.
  - Results suggest that the power of the publicity channel is unique to Robert Parker’s reviews.
Future Work

- Results highlight heterogeneity of responses across different wines
- Investigate which characteristics of the wine types cause the market to “play with” the expert versus “play against” the expert on either the quality information or other components
- Investigate this heterogeneity across geographic lines as well as across wine characteristics by using our collected text from CellarTracker and expert reviews
Thanks!

Questions?
Construct a unique time series panel combining auction prices, online reviews, and expert reviews:

- Collaborated with *Wine Market Journal* and CellarTracker.com to generate a unique dataset of 355 1990-2010 vintage wines that are rich in both auction price and social media review data (2004Q1-2017Q2)
  - Identified wines with 20 consecutive quarters of auction data since 2004 → 873 wines and 30,258 quarters of auction price data
  - Subset from the 873 those with at least 16 consecutive quarters that contain both tasting note scores and auction price averages → 355 wines with 10,109 quarters of auction price and CellarTracker data
- Collected expert reviews on the sample from Robert Parker’s RobertParker.com, Jancis Robinson’s JancisRobinson.com, and Anthonio Galloni’s Vinous.com
  - 240 Parker, 399 Robinson, and 146 Vinous reviews in the relevant 10,109 quarters
Data: Vintages

Histogram of Vintages for the Sample of 355 Wines

via Albright et al. (2018)
Data: Reviews

RobertParker.com Scores

JancisRobinson.com Scores

Vinous.com Scores

via Albright et al. (2018)
Signal Extraction Problem in the Case of High-End Wine

- Quality $q_t$ and other factors $\tau_t$ influence utility and hence demand, but are unobserved.
- Expert reviews depend on other factors (established reputations of the wine producer, etc.) and taste-testing for quality.
- Expert reviews $\varrho_t$ provide a signal of $q_t$ and $\tau_t$ with exogenous noise $\epsilon_\rho$:

$$\varrho_t(q_t, \tau_t) = p_0 + p_1 q_t + p_2 \tau_t + \epsilon_\rho$$
Amateur reviews are posted by wine enthusiasts who have sampled the product and are knowledgeable consumers.

Their knowledge of $\tau_t$ is less complete than the experts, but they somewhat reflect other factors in their reviews by conditioning their signal on the log of prices from previous auctions.

Amateur reviews $\gamma_t$ provide a signal of $q_t$ and (via price) a signal of $\tau_{t-1}$ (that is, other factors but with a lag) with exogenous noise $\epsilon_{\gamma}$:

$$\gamma_t(p_{t-1}, q_t) = k_0 + k_1 p_{t-1} + k_2 q_t + \epsilon_{\gamma}$$
Stationary price series is produced conditional on contemporaneous values of quality and lagged values of other factors.

The two are associated with noisy signals, for which both the social media and expert reviews provide information.

Purely stochastic components of these noisy signals are denoted by the orthogonalized vector of white noise shocks $\epsilon_{it} = (\epsilon^p_{it}, \epsilon^\kappa_{it})'$.

Identification: no direct immediate impact effect from $\epsilon^\kappa_{it}$ to the average CellarTracker score in the period of the shock.

Since $\gamma_t$ depends linearly on lagged prices $p_{t-1}$ and current quality $q_t$ (via model).
Empirical Strategy: Model and Shocks

Combine model intuition with panel structural VAR approach (Pedroni 2013)

- Wine quality evolves smoothly, but new information arriving about its quality comes in shocks = “quality information shocks” = $\epsilon_{it}^\rho$
  - Think noisy shock associated with $q$ from model

- Wine price is impacted by other factors that influence supply and demand for wine after it has been produced = “other shocks” = $\epsilon_{it}^\kappa$
  - Think noisy shock associated with $\tau$ from model

Resulting identification strategy: no immediate impact effect from $\epsilon_{it}^\kappa$ to the average CellarTracker score in the period of the shock
Empirical Strategy: Panel SVAR Set-Up

$\Delta z_{it}$ 2 × 1 vector of panel time series variables observed over time periods $t = 1, \ldots, T$ for units $i = 1, \ldots, N_t$

- $\Delta z_{1, it} =$ CellarTracker review score average for wine $i$ at time $t$
- $\Delta z_{2, it} =$ natural log of the auction price average for wine $i$ at time $t$

For each wine $i$, estimate standard reduced form VAR:

$$\Delta z_{it} = R_{i1} \Delta z_{it-1} + \ldots + R_{iP_i} \Delta z_{it-P_i} + \mu_{it}$$

I.e., $R_i(L) \Delta z_{it} = \mu_{it}$, $R_i(L) = I - \sum_{j=1}^{P_i} R_{ij} L^j$
Empirical Strategy: Identification Strategy

To construct impulse responses to our economic shocks, $\epsilon_{it} = (\epsilon_{it}^\rho, \epsilon_{it}^\kappa)'$, we need to obtain the structural VMA representation of the data $\Delta z_{it} = A_i(L)\epsilon_{it}$ with $A_i(L) = \sum_{j=0}^{Q} A_{ij}L^j$.

Recall identification: no direct immediate impact effect from $\epsilon_{it}^\kappa$ to the average CellarTracker score in the period of the shock.

- Set restriction on the short run impact matrix such that $A_i(0)_{12} = 0 \forall i$ (leaves future periods free to respond).
More on Panel SVARs: (1) estimate reduced form composite/common VARs

- Estimate a reduced form VAR for each member of the panel
- Recover the composite shocks associated with each member of the panel

\[ R_i(L) \Delta z_{it} = \mu_{it} \] with \[ R_i(L) = I - \sum_{j=1}^{P_i} R_{ij} L^j \] estimate this form using single-equation OLS for the 2 variables in \( \Delta z_{it} \) separately for each member of the panel

i.e., for each \( i \) regress \( \Delta z_{1,it} \) on \( \Delta z_{1,it-1}, \Delta z_{2,it-1}, \Delta z_{1,it-2}, \Delta z_{2,it-2}, \ldots, z_{1,it-P_i}, \Delta z_{2,it-P_i} \) and regress \( \Delta z_{2,it} \) on \( \Delta z_{1,it-1}, \Delta z_{2,it-1}, \Delta z_{1,it-2}, \Delta z_{2,it-2}, \ldots, z_{1,it-P_i}, \Delta z_{2,it-P_i} \)

- Obtain coefficients in 2 \( \times \) 2 matrices \( R_{i1}, \ldots, R_{iP_i} \)
- Lag truncation can differ by panel members

- Estimate a reduced form VAR for the estimated time effects, attempting to recover the common shocks associated with these

\[ R(L) \Delta \tilde{z}_t = \tilde{\mu}_t \] with \( R(L) = I - \sum_{j=1}^{\tilde{P}} \tilde{R}_j L^j \) estimate this form by OLS separately for each member of the panel
More on Panel SVARs: (2) obtain structural shock estimates $\epsilon_{it}$ and $\bar{\epsilon}_t$

We want the structural VMA representation of the data $\Delta z_{it} = A_i(L)\epsilon_{it}$ with $A_i(L) = \sum_{j=0}^{Q} A_{i,j} L^j$

- Unique mapping (in the absence of identifying restrictions) from the reduced form VAR estimates $R_i(L), \bar{R}(L), \mu_{it}, \bar{\mu}_t$ to the structural form VMA components $A_i(L), \bar{A}(L), \epsilon_{it}, \bar{\epsilon}_t$: $A_i(L) = R_i(L)^{-1} A_i(0)$, $\epsilon_{it} = A_i(0)^{-1} \mu_{it}$, $\bar{A}(L) = \bar{R}(L)^{-1} \bar{A}(0)$, $\bar{\epsilon}_t = \bar{A}(0)^{-1} \bar{\mu}_t$

- Mapping computed individually once for each wine of the sample to obtain the composite shocks, and then once analogously for the cross sectionally average data to obtain the common shocks

Recall identification: no direct immediate impact effect from $\epsilon_{it}$ to the average CellarTracker score in the period of the shock

- Set restriction on the short run impact matrix such that $A_i(0)_{12} = 0 \ \forall i$ (leaves future periods free to respond)
- Same mapping as a conventional Cholesky orthogonalization (since $A_i(0)$ is upper triangular)
More on Panel SVARs: (3) compute member-specific impulse responses to unit shocks, $\tilde{A}_i(L)$, $\tilde{\tilde{A}}_i(L)$

First, compute $\Lambda_i$ as a diagonal matrix whose diagonal elements are the correlations between $\epsilon_{it}$ and $\bar{\epsilon}_t$ for each member $i$. Then,

$$\tilde{A}_i(L) = A_i(L)\Lambda_i$$

$$\tilde{\tilde{A}}(L)_i = A_i(L)(I - \Lambda_i\Lambda'_i)$$

We plot $\tilde{\tilde{A}}(L)_i$ in this presentation and in the paper.
More on Results

- Present reaction of endogenous variables at time of shocks and during subsequent time periods
- Present idiosyncratic responses to control for cross-sectional dependencies $\tilde{A}_i(L)$
- Different response for each wine; depict interquartile range (25th, median, 75th) and mean of responses to one unit increase in expert review
- Illustrate for Parker, Robinson, and Vinous subsamples; they must have an expert review which occurs sometime after the first 8 periods but before the last 4 periods
  - This leaves 115 wines with such Parker reviews, 136 for Robinson, and 61 for Vinous.