Agricultural and Resource Economics Review (2024), **53**, 66–86
doi:10.1017/age.2023.11

RESEARCH ARTICLE

Tasting and consumer demand for wine: do peers and experts matter?

Nadeeka Weerasekara and Nadia A. Streletskaya

Applied Economics Department, Oregon State University, Corvallis, OR, USA
Corresponding author: Nadia A. Streletskaya; Email: nadia.streletskaya@oregonstate.edu

(Received 30 April 2022; revised 28 February 2023; accepted 3 March 2023; first published online 13 October 2023)

Abstract

Expert and peer reviews and popularity are freely available both on the Internet and in printed materials for a variety of food products. Using two experimental studies with non-hypothetical tastings and auctions, we explore the impact of peer tasting popularity, actual peer ratings, and expert ratings on demand for wines consumers can or have tasted. We find that higher own wine ratings are associated with higher willingness to pay (WTP). Morevoer, higher peer and expert rating scores increase consumer WTP for wine even after controlling for the impact of consumers' own ratings. Observed peer popularity also increases WTP for preferred wines.

Keywords: consumer demand; expert ratings; peer effects; ranking; tastings

JEL: D12; D91; Q13

Introduction

Peer groups, family members, experts, teachers, and strangers can all impact individual consumer purchasing decisions (Burnkrant and Cousineau 1975; Bearden and Etzel 1982; Childers and Rao 1992; Streletskaya 2022; Griskevicius et al. 2010; among others). At the same time, tasting and product sampling are well-established product promotion strategies (Jain et al. 1995; Heiman et al. 2001), particularly for highly differentiated food products (Lammers 1991; Stiletto et al. 2021). The overlap between third-party information on product quality and tasting experiences is less understood. While many economics models assume that both sampling and external quality ratings allow the consumer to better evaluate quality of the product to make a purchase decision (e.g., Erdem and Keane 1996), some research suggests that peer and expert effects can persist when controlling for underlying quality (Reinstein and Snyder 2005).

In this paper, we explore how expert and peer information affects consumer willingness to pay (WTP) in presence of tastings. We find that higher peer or expert valuation both increase consumer WTP after tasting; moreover, when tasting choice is endogenous to consumer preferences, the WTP for tasted wine is further increased by its popularity among peers. On the other hand, we find that observed peer popularity decreases the WTP for wines consumers who choose not to taste, suggesting that peer popularity can have an asymmetric impact on demand, possibly driven by confirmation bias (Zaleskiewicz and Gasiorowska 2018).

Wine sales have historically relied on expert-generated ratings, with experts displaying significant disagreements in their evaluations of the same wines (Oczkowski and Doucouliagos 2015). Wine experts incorporate their individual taste preferences in overall valuations, and while general alignment of preferences between the expert and consumer is important for consumer decision-making (Cardebat and Livat 2016), it is not always clear to the consumer. In general, expert evaluations tend to be trusted more when they are congruent with their own evaluation (Flanagin and Metzger 2013), a manifestation of consumer confirmation bias searching for product information (Zaleskiewicz and Gasiorowska 2018). The experimental design used in our studies allows us to separately evaluate the impact of congruent and incongruent judgments and compare peer effects to expert effects on consumer WTP.

Study 1 is based on mandatory tasting and evaluation of four Pinot Noir wines, with two treatments that additionally provide the average peer tasting evaluation and expert wine evaluation during consumer WTP elicitation. In study 2, we allow participants to first select the wines they would like to taste for $1 out of six available different varietals. Participants observe the choices for tasting made independently by their peers, and we elicit their WTP for all wines, both tasted and not tasted. The different designs of the two studies allow us to present a more complete picture of the impact of tasting, peer, and expert information on consumer demand for wine.

The rest of the paper proceeds as follows. We introduce and discuss the existing literature on peer effects and tasting and their impact on consumer demand, highlighting some of the current literature gaps; we then detail the design, estimation, and detailed result of study 1, followed by the study 2. We summarize the overall results and discuss managerial and research implications of our study.

Background

Consumer access to peer reviews, expert ratings and evaluations, and comparison test results has been steadily growing over the past 20 years (Chen and Xie 2008). Their relative impacts on consumer demand vary and can depend on the setting, consumer familiarity with the medium, and number of reviews (Smith et al. 2005; Chakraborty and Bhat 2018; Zhu et al. 2018).

In the wine industry, information about product quality reduces consumer reliance on price signals of quality (Lynch and Ariely 2000; Chung and Saini 2022). The use of expert ratings and tasting critiques is common, while the use of peer ratings is less ubiquitous. Expert wine ratings are generally considered to be a good indicator of product quality (Benjamin and Podolny 1999). Cuellar and Claps (2013) find that a one-point increase in Wine Spectator rating is associated with an approximately 7% increase in price for wines. On the other hand, some studies have found consumer skepticism around wine awards (Neuninger et al. 2017) and suggest that the usefulness of expert reviews is limited for consumers (Marks 2015; Oczkowski and Doucouliagos 2015). Friberg and Grönqvist (2012) find that while positive expert reviews increase consumer demand for wine, neutral reviews have small positive effects and negative reviews do not affect consumer demand.

We know less about the effect of peer-sourced reviews on wine demand. Wu et al. (2021) find that consumers can infer the expertise of online wine reviewers by assessing the variance of their past reviews. Thrane (2019) finds that peer recommendations matter for red wine choice, and that expert quality reviews matter more for non-peer-recommended wine, but the relative importance of peer and expert recommendations is not explored.

Food sampling and free tasting at the point of purchase are often used as a promotion strategy (Jain et al. 1995; Heiman et al. 2001). Tasting rooms are generally considered very important in the winery business model (Alonso et al. 2008), with winery tasting rooms encouraging wine tourism and future purchases of regional wines (McCole et al. 2018). Free tastings in particular seem to generate higher level of sales (Kolyesnikova and Dodd 2009), and having winery and cellar door tasting rooms helps to build brand loyalty and interest in wine (Fountain et al. 2008). While wine tastings should theoretically allow consumers to better match any tasted bottle with their particular taste preferences, little is known about the overall impact of tasting wine on consumer WTP for it.

Product sampling and third-party evaluation information are often present for the same products. Munnukka et al. (2016) find that own product experience reduces the effectiveness of peer-endorsement advertising. Alemu and Olsen (2020), on the other hand, suggest that negative peer evaluation reduces acceptance of potentially stigmatized foods, even after a positive tasting experience. In the wine setting, Buonnanno et al. (2010) find that existing peer and expert scores can significantly impact own food and wine scores at blind tastings.

Independent of the source of third-party information, when product sampling is possible or when consumers have their own experiences with the reviewed product, the congruence of own experience and the review can have an important impact on consumer trust and decision to incorporate the review information in their own evaluation process (Flanagin and Metzger 2013; Cardebat and Livat 2016). Consumer choice to incorporate or disregard external evaluation cues is commonly driven by confirmation bias (Metzger et al. 2010).

Relevant hypotheses

Based on the existing research reviewed in the background section, we formulate some relevant hypotheses and present them below.

Information provision often affects consumer uncertainty and ambiguity and both shift and rotate consumer demand curves (Johnson and Myatt 2006; Liaukonyte et al. 2015); at the same time, the effect of sensory information provision after tasting is unclear as consumers should have full private information on the sensory match. We can test the impact of third-party information by comparing consumer bids and their distribution in the control and treatment groups.

H1. Provision of peer and expert ratings changes the distribution of consumer bids for the same product even after tasting.

While the above hypothesis focuses on whether information provision can affect aggregate consumer demand for wine even after tasting, from a managerial standpoint, it is important to see the impact of owns rating on consumer WTP, alongside peer and expert information.

H2. Consumers exhibit higher WTP for wine they rated highly after tasting or selected for tasting.

H3. Positive expert and peer information increases consumer WTP for wine, while negative peer and expert information reduces consumer WTP for wine.

Previous research suggests that consumers are prone to confirmation bias and tend to value expert opinions on wine more than peer.

H4. Impact of peer and expert information on consumer demand differs.

H5. Peer and expert information congruent with consumer own evaluation of wine have a differential impact on consumer WTP.

We use two experimental studies with wine tasting and demand elicitation via an incentive-compatible mechanism to examine the hypothesis outlined above. Both studies were IRB-approved as exempt and took place in an experimental economics lab at a large Pacific Northwest University. Recruitment was conducted through email solicitations to the existing pool of the experimental economics lab with details about the study. All participants were screened on having had previous wine consumption and winery visit experience, age over 21 years (to comply with state regulations), and pregnancy status (IRB excluded pregnant participants due to the potentially increased risk associated with alcohol consumption). On average, between 12 and 14 years of wine drinking experience was reported. Over half of our sample in each study reported drinking wine at least once a week, while an additional 30–37% of the sample drank wine more occasionally, on special occasions. Participation in each study was associated with a $35 endowment, that participants could keep in full if no wine was purchased. We discuss the design, sample, and estimation approaches of each study in detail in the next sections.

Study 1: average peer rating and expert rating

Methods and experimental design

This study had two treatment groups (1: providing the average peer rating for each wine after the tasting, and 2: providing expert ratings sourced from the Wine Spectator) and one control group, where participants were only reminded of their own rating for the wine during the WTP elicitation stage.

Each session in the experiment consisted of a wine tasting stage and a computerized WTP elicitation stage for the all wines in the experiment. Tasting stage setup was similar in all groups, and only the additional information provided during the auction on wine ratings differed across the treatment and control groups.

During the tasting stage, all participants tasted and rated the same four wines sequentially, with the order of wines randomized for each tasting session. Each session included up to nine participants at a time. To rate the wines, participants used a five-star system common in many consumer rating applications, where each star level was described using a corresponding Wine Spectator scale. The Wine Spectator's 100-point scale is divided into six categories: 100 to 95 points range represents a "classic: a great wine," 94 to 90 points are awarded to wine that is "outstanding: a wine of superior character and style," 89 to 85 point signify a wine that is "very good: a wine with special qualities," 84 to 80 describe a wine that is "good: a solid, well-made wine," while 79 to 75 points are assigned to "mediocre [wine]: a drinkable wine that may have minor flaws," while anything below 74 points is "not recommended" by the Wine Spectator. We use these category descriptions for our five-star rating, with one star described as the mediocre wine category and five stars described as the top category wine. Figure 1(A) presents the rating description seen by participants for each wine.

The bottles used in the first experiment were masked, with labels and identifying brand features covered universally and similarly across all bottles, to limit brand and packaging design impacts on tasting and demand elicitation. This masking also prevented respondents from seeing information on vintage, region, and any descriptions of the wine usually present on the wine bottle. All four wines were Pinot Noirs from different wineries and vintages, chosen to represent a broad range of Wine Spectator expert rankings. Finding and sourcing even mediocre wine is quite difficult, as only 49 wines among the 2016–2021 vintages were rated at or below 79 points, out of total of 43,860 wines rated for the same period (Wine Spectator 2021). This suggests that out of all

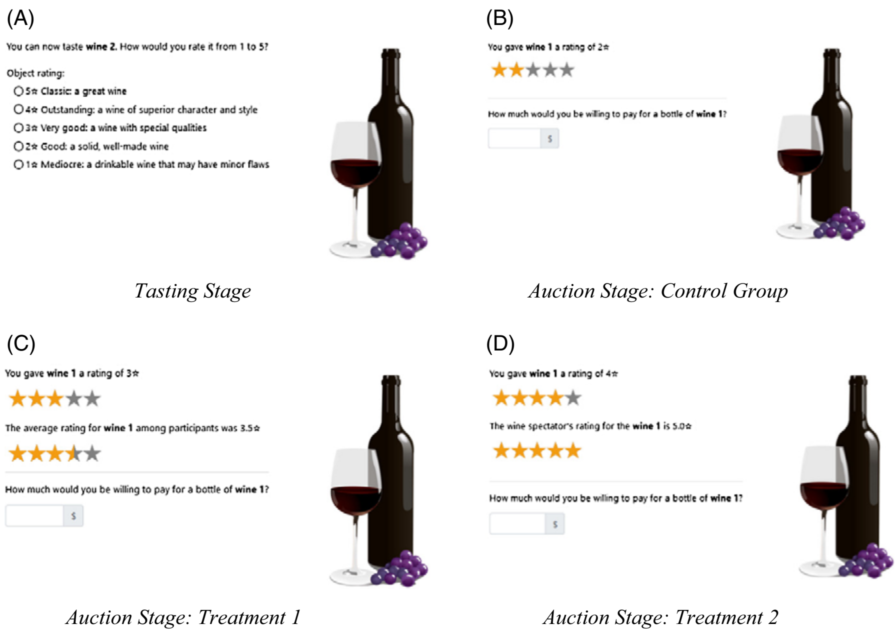

Figure 1. Computer interface for study 1.

reviewed wines, only under around 0.11% were rated as mediocre or not recommended. Only 3 wines out of these 49 were rated below 75 (not recommended). As a comparison point, 1,545 wines, or around 3.52%, were rated as Classic, the highest category, in the same time period. In essence, most wines reviewed in the Wine Spectator are rated 80 points and above. For our experiment, we were able to source wines rated between two and five stars, one wine per each of these star categories.

After wine tasting and rating were completed for all four wines, we used computerized Becker-deGroot-Marschak (BDM) (Becker et al. 1964) mechanism auctions for demand elicitation. The BDM was selected as the elicitation method because subjects do not bid against each other but rather submit a sealed bid for wine. Once all bids are submitted in a session, we randomly chose a market price for one randomly selected wine bottle (from a distribution around the retail price of the wine). If a participant's bid is equal to or exceeded the randomly drawn price, they receive the wine bottle at the randomly drawn price, and not at the value of their bid; otherwise, no transaction results from the auction. This method allows us to reliably incentivize participants to bid their true maximum WTP for all auctioned items.

At the start of the auction stage, participants were informed that all wines in the experiment retailed for between $15 and $35 to bound their price expectations, in line with other work on wine WTP elicitation (Streletskaya et al. 2019). The information provided during the auction stage differed based on control or treatment assignment, with the computer screens provided in Fig. 1B–D. In the control group, the bidding screen reminded participants of their own rating for the wine submitted during the tasting stage, as shown in Fig. 1 B. In the peer treatment group, participants also saw the average rating, down to half-star approximation, of other people in the room, as well as their own rating, as shown in Fig. 1C. In the expert treatment group, participants saw the Wine Spectator rating for the wine, in addition to their own wine rating, Fig. 1D.

Once all participants submitted their bids to all four wines, we revealed the randomly drawn binding auction and the randomly drawn clearing price for that auction. Participants who submitted a bid higher than or equal to the clearing price receive the wine bottle for the binding auction at the clearing price and keep the rest of their participation payment. Participants with bids lower than the clearing price keep $35 of their participation payment and do not receive a wine bottle. This approach to market clearing with multiple product auctions is generally considered incentive-compatible under monotonicity assumptions (Azrieli et al. 2018). All participants took part in a practice round of bidding for a one-dollar bill to illustrate the incentives to reveal one's maximum WTP.

An extensive sociodemographic survey was administered to all participants after the auction bids were submitted. At the end of the experiment, the market was cleared and the subjects were given their compensation.

Sample and estimation approach

One-hundred seventy-three wine drinkers over 21 years old participated in this experiment. Detailed summary statistics for the overall sample, and treatment and control groups, are presented in Table 1. Participants in the overall sample varied in age between 21 and 65 years old, with average age of around 33 years old for the full sample. Some difference is present for participant age in the control group compared to both treatment groups, and the average participant age in both treatments is not significantly different from each other. While overall the descriptive statistics look similar between all groups, the nature of random assignment with a finite sample yields some variation across the groups.

Pairwise mean comparison of bid values and own ratings with Bonferroni correction across participant groups suggests no difference at the 5% significance level. On average, the study participants had significant experience with wine, drinking wine for over 10 years, but that was not reflected in the scores of the objective wine knowledge test. On average, respondents scored below 50%, which is in line with general consumer wine knowledge (Aqueveque 2015). Our participants regularly reported trying new wines, which is common for a highly differentiated product market. Finally, it is interesting to note that on average, own ratings were significantly lower than the expert ratings for all wines, with consumers seemingly harsher than experts in wine quality evaluation.

We use a series of standard Tobit model specifications, with clustered standard errors by participant, to estimate consumer WTP for wine in the presence of treatment, own, peer, and expert ratings of wine, depending on specification:

$$\begin{cases} WTP^*_{ijt} = \alpha_{it} + \beta_{it} OwnRating_{ij} + \beta_{expert} ExpertRating_j + \beta_{peer} PeerRating + \\ \qquad + \beta_t Treatment + \sum_i \gamma_l X_{li} + \varepsilon_{ijt} \\ WTP_{ijt} = \max\left(WTP^*_{ijt},\ 0\right) \end{cases}$$

Here, subscript i refers to a participant, j to particular wine, and t refers to experiment assignment group. The constant is denoted as α_{it}, *PeerRating* and *ExpertRating* provide the average in wine peer rating or the expert wine rating, respectively, and are equal to 0 when no peer or expert information was available to participants. *OwnRating* includes participant i's own rating for each wine j. *Treatment* refers to the treatment (1 and 2) and control (0) groups. γ_l represents the marginal effect of sociodemographic or bottle

Table 1. Descriptive statistics: Means and (Standard Deviations) of demographic variables by treatment

	All	Control: own rating only	Treatment 1: own rating + group's average rating	Treatment 2: own rating + Wine Spectator's rating
WTP ($)	9.58 (6.77)	9.47 (6.82)	9.51 (5.96)	9.77 (7.50)
Own rating	2.214 (0.385)	2.074 (0.386)	2.246 (1.044)	2.309 (1.100)
Mean peer rating (in tasting group)	–	–	2.246 (.303)	–
Expert rating	–	–	–	3.5 (1.120)
Age (years)	33.53 (11.91)	37.00 (14.20)	31.90 (9.69)	31.98 (10.97)
Gender (%)				
Female	70.52	72.22	68.33	71.19
Male	28.32	25.93	30.00	28.81
Other	1.16	1.85	1.67	–
Education (%)				
High school graduate	1.73	1.85	3.33	–
Some college	17.34	14.81	21.67	15.25
Associate degree	4.62	5.56	3.33	5.08
Bachelor's degree	35.84	29.63	26.67	50. 85
Graduate degree	40.46	48.15	45.00	28.81
Income category (%)				
Less than or equal $24,999	35.84	27.78	40.00	38.98
$25,000–$49,999	23.70	18.52	21.67	30.51
$50,000–$99,999	24.86	35.19	20.00	20.34
Greater than or equal to $100,000	15.61	18.52	18.33	10.17
Wine knowledge test score (out of 100)	38.15 (22.80)	40.37 (22.66)	35 (23.03)	39.32(22.44)
Try new wines (%)				
Never	2.89	1.85	0.00	6.78
Sometimes	48.55	57.41	48.33	40.68
Regularly	36.99	31.48	35.00	44.07
Most of the time	10.98	9.26	15.00	8.47
Always	0.58	0.00	1.67	0.00
Wine consumption frequency (%)				
Never	0.58	1.85	0	0
On special occasions	36.99	31.48	41.67	37.29

(*Continued*)

Table 1. (*Continued*)

	All	Control: own rating only	Treatment 1: own rating + group's average rating	Treatment 2: own rating + Wine Spectator's rating
Only on weekends	15.03	12.96	16.67	15.25
Once a week	31.79	29.63	30	35.59
3–5 times a week	15.03	24.07	11.67	10.17
Everyday	0.58	0	0	1.69
Years drinking wine	11.61 (10.24)	14.07 (11.24)	10.38 (8.546)	10.59 (10.52)
# of subjects	173	54	60	59
# of bids = $0.00	65	21	18	26

attribute l on WTP, while X_{li} is the level of attribute l for individual i, and finally, the error term is $\varepsilon_{ijt} \sim N(0,1)$.

Postestimation tests and the significance of parameter estimates, in some cases, are used to test the hypotheses of interest. In addition, we use a set of Kolmogorov–Smirnov (KS) distribution tests to evaluate the equality of consumer bid distributions for the control and treatments group.

Estimation results

H1. Provision of peer and expert ratings changes the distribution of consumer bids for the same product even after tasting.

We use our full sample to examine H1. The results of KS tests suggest that the distributions of consumer WTP for wine are not statistically different between the control group and participants receiving peer or expert rating information (Combine KS D: 0.0299, p-value 0.999). No differences in the WTP distribution between control and treatment groups hold for each individual wine bottle evaluated (bottle 1: Combined KS D 0.0853, p-value 0.950; bottle 2: Combined KS D 0.1184, p-value 0.675; bottle 3: Combined KS D 0.0563, p-value 1.000; bottle 4: Combined KS D 0.0979, p-value 0.869). Our Tobit regression results, with own rating (specification 2), and with demographic controls for gender, age, education, and race (specification 3), and without (specification 1), are similar and suggest no difference in consumer WTP for wine in presence or absence of peer and expert valuation information. Overall, we use data from all 173 participants in all of our specifications, which keeps the number of clusters the same across specifications, as all consumers have data on all controls used in the specification. The detailed estimation results are presented in Table 2.

H2. Consumers exhibit higher WTP for wine they rated highly after tasting or select for tasting.

Table 2 presents a highly significant and positive estimate for the impact of consumer own rating on WTP for wine. Specifically, a one-star increase in own rating is associated with a $2.86 increase in consumer WTP for the wine, when controlling for respondent demographic characteristics.

Table 2. H1, Tobit estimation results, impacts of expert and peer information on consumer WTP

	(1) bid	(2) bid	(3) bid
Control (no peer/expert information)	−0.184	0.418	0.523
	(1.005)	(0.945)	(0.932)
Own rating	–	2.982***	2.826***
		(0.301)	(0.277)
Controls	none	none	age, gender, education, race
N	692	692	692
Left-censored	65	65	65
Clusters for errors	173	173	173
Pseudo R-squared	0.0000207	0.0321	0.0394
Log-likelihood	−2217.0	−2145.7	−2129.6
p-Value for model test	0.854	9.52e-21	1.76e-29

Standard errors are in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We continue to analyze our data by limiting the data in consideration to respondents who receive either peer or expert valuation to focus on the impact of peer and expert information. This leaves 119 participants in our sample. The results from a set of Tobit estimations for this sample are provided in Table 3.

Again, consistently, own rating of wine is estimated to play a significant role in consumer WTP formation. An additional star in own rating is associated with between $2.74 and $3.33 increase in consumer WTP for the bottle.

H3. Positive expert and peer information increases consumer WTP for wine, while negative peer and expert information reduces consumer WTP for wine.

Controlling for own rating for the wine, we estimate that positive peer and expert ratings significantly increase consumer WTP for the wine (specifications 1–3, model 2). A one-star higher peer evaluation for the wine increases consumer WTP by between $1.79. and $1.96, when controlling for own wine rating. A one-star higher expert rating is similarly associated with a $1.15 to $1.16 increase in consumer WTP for the wine.

H4. Impact of peer and expert information on consumer demand differs.

The difference between the impacts of peer and expert rating information on consumer WTP is not significant at the 5% level. The *p*-values of the *F*-test for the equality of coefficients are 0.157, 0.0717, and 0.0677 for specifications 1–3 (Table 3), respectively. We conclude that both peer and expert valuation impacts consumer WTP for wine.

Another way to look at the impact of outside information in presence of tasting is to focus on the impact of the difference between peer or expert rating with own rating of the participant. We take this approach in specifications 4–5 (Table 3). The results are similar and consistent with results from the base specifications 1–3 and reflect the fact that while higher peer and expert evaluations increase consumer WTP, when own rating for the wine was lower compared to expert or peer evaluation, consumers exhibit lower WTP for wine.

Table 3. Tobit estimation results, expert and peer impacts on consumer WTP

	(1) bid	(2) bid	(3) bid	(4) bid	(5) bid
Own rating	2.724***	2.712***	3.331***	–	–
	(0.373)	(0.331)	(0.521)		
Average peer rating	1.796***	1.938***	1.964***	5.098***	5.677***
	(0.498)	(0.461)	(0.459)	(0.596)	(0.739)
Expert rating	1.161***	1.147***	1.162***	4.319***	4.889***
	(0.265)	(0.265)	(0.265)	(0.563)	(0.681)
Rating difference with peers	–	–	–	−2.105***	−2.698***
				(0.455)	(0.610)
Rating difference with experts	–	–	–	−3.185***	−3.741***
				(0.482)	(0.614)
Own rating two stars and fewer	–	–	1.582*	–	1.462
			(0.929)		(0.927)
Controls	none	age, gender, education, race			
N	476	476	476	476	476
Left-censored	44	44	44	44	44
Clusters for errors	119	119	119	119	119
Pseudo R-squared	0.0308	0.0356	0.0361	0.0367	0.0372
Log-likelihood	−1478.2	−1470.9	−1470.1	−1469.2	−1468.4
p-Value for model test	6.87e-15	3.11e-26	3.21e-25	9.96e-26	7.09e-25

Standard errors are in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The important takeaway here is that for both peer and expert information, *F*-tests (*p*-values 0.0, 0.0) suggest that the overall impact of positive peer and expert evaluation overweighs the impact of the disagreement between own and external ratings, leading to, on average, higher WTP. This is in line with results from specifications 1–3. Similar to alternative specifications, we do not observe any difference between peer and expert effects (*F*-test *p*-value 0.7335). Specifications 3 and 5 both include a dummy variable control to mark the wines consumers rated at two stars or below, to control for potential strong dislike. The results are consistent between all specifications.

H5. Peer and expert information congruent with consumer own evaluation of wine have a differential impact on consumer WTP.

To investigate the impact of the scale of difference between peer and expert rating and own rating, we estimate a final set of Tobit models that include squared difference between the own and external ratings, in addition to the difference in ratings non-squared. As peer ratings are on average lower than expert ratings, this affects the scale of the square difference measure, and we separately estimate the model for the peer and expert treatment groups. The results are presented in Table 4. A significant coefficient on the squared

Table 4. The impact of rating congruency between own and external ratings

	Peer rating group		Expert rating group	
	(1)	(2)	(3)	(4)
	bid	bid	bid	bid
Own rating	3.720***	3.804***	4.687***	4.629***
	(1.238)	(1.139)	(0.684)	(0.620)
Difference external – own rating	2.101*	2.018*	1.233***	1.273***
	(1.231)	(1.211)	(0.464)	(0.431)
Difference external – own rating squared	0.815	0.682*	0.0322	0.0156
	(0.501)	(0.399)	(0.142)	(0.135)
Controls	None	age, gender, education, race	none	age, gender, education, race
N	240	240	236	236
Left-censored	18	18	26	26
Clusters for errors	60	60	59	59
Pseudo R-squared	0.0269	0.0445	0.0388	0.0415
Log-likelihood	−727.9	−714.7	−740.4	−738.3
p-Value for model test	0.0000228	2.09e-10	2.03e-10	1.75e-09

Standard errors are in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

difference suggests that as the difference increases, its impact increases or decreases. In other words, as external and own ratings become less congruent, their impact changes. We do not find strong support for this hypothesis. The results are consistent between different specifications, with no strong support for the difference in effect between incongruent ratings and similar ratings.

Study 2: average peer rating and expert rating

Methods and experimental design

The main difference between study 1 and study 2 lies in the ability of participants to select some wine for tasting and forgo others in study 2. Additionally, we do not provide explicit rating information and rely on participants' own observations of peer tasting popularity. The aim of this design change is to modify the experimental design closer to common setup of tasting experiences when explicit peer and expert ratings are not available, and when consumers choose the wines to taste. Specifically, while explicit ratings from peers and experts are available for some wines, especially when the rating is high and used as a promotional strategy, and consumers are able to look them up for particular wines online, in most tasting rooms consumers are more likely to rely on other popularity cues, such as the number of other visitors examining or tasting a particular wine (Streletskaya 2022). Six wines of six different varieties were presented for tasting and bidding in each experimental session. The experiment started with participants arriving in the lab, reading and signing experimental instructions and the consent forms, and being endowed with $35.

Participants observed a list of six wines available for tasting and were instructed to select the wine they would like to taste by marking them on their screens. Each wine cost them $1 to taste, to mimic the tasting fee common in wineries. Compared to study 1, we do not mask the bottle and labels of the wines used in this experiment, further moving the environment closer to that of an actual tasting room. However, the selection of the wines remains the same and fixed across the treatment groups, allowing for experimental identification of treatment effect. Participants could not discuss or observe tasting choices of other participants before submitting their own choices. Once all participants submitted their choices, the experimenter sequentially went through all the six wines in the tasting session, pouring one wine at a time to all participants who selected the wine. Thus, during the actual tasting participants observed the general popularity of each wine among their peers, with up to six participants in each experimental session. The tasting itself was organized in the manner described in study 1.

Once the tasting concluded, consumers went through a series of computerized BDM mechanism auctions for six wines, with the procedure outlined in detail in study 1. While participants differed on the amount of sensory descriptions and information available about the wines, in this experiment we focus solely on the impact of observing wine popularity on consumer WTP on average.

An extensive sociodemographic and wine consumption survey was administered to all participants after their completion of the auctions, and the subjects were given their compensation and wine, according to the auction clearing results, at the end of the experiment.

Data were analyzed using the Tobit estimation approach detailed in study 1.

Estimation results

On-hundred eighty-nine participants who were over 21 years of age and had previous wine tasting experience took part in the study. In general, the demographic characteristics of the sample (see Table 5) are comparable to those of study 1 sample. Participants, on average, had almost 14 years of experience drinking wine and tried new wines consistently.

Participants tasted approximately half of the wines available for tasting (48%), and the average WTP for these wines did not differ significantly from study 1, averaging at $10.12. On average, each experimental session included five participants, implying each participant on average observed the choices of approximately four peers. In line with the general tasting level, most participants observed on average half of their peers tasting each wine, with sizable standard deviation. Two sessions during experiment only had one participant. We drop these sessions in the analysis, as the single participant by definition did not observe any peer social cues.

The following general hypotheses, formulated earlier in the paper, with originarling preserved, are examined in study 2.

H2. Consumers exhibit higher WTP for wine they rated highly after tasting or selected to taste.

In study 2, we do not directly collect information on wine ratings, as not all wines are tasted and no rating information is provided to participants or revealed by the participant to the experimenter. However, we allow consumers to opt into a costly voluntary tasting. The WTP for tasting indicates a relatively higher preference for the chosen wine, and it should be correlated with higher WTP. Note that this is an endogenous relationship, compared to study 1, where participants were assigned to taste all wines. The Tobit

Table 5. Descriptive statistics of the sample, study 2

Wines tasted, on average (%)	47.88
Bids ($)	10.12 (7.87)
Number of others in tasting session, excluding participant	3.95 (1.23)
Average percentage of people tasting a wine, excluding participant, per wine session	47.77 (29.39)
Average number of people tasting a wine, excluding participant, per wine session	1.89 (1.26)
Age (years)	35.36 (13.68)
Female (%)	62.90 (0.48)
Education (%)	
High school graduate	0.53
Some college	11.11
Associate degree	4.23
Bachelor's degree	39.15
Graduate degree	44.97
Income category (%)	
Less than or equal $24,999	39.15
$25,000–$49,999	20.63
$50,000–$99,999	23.81
Greater than or equal $100,000	16.40
Wine knowledge test score (out of 100)	36.74 (13.82)
Try new wines (%)	
Never	2.65
Sometimes	54.50
Regularly	31.75
Most of the time	10.05
Always	1.06
Wine consumption frequency (%)	
Never	0.53
On special occasions	30.16
Only on the weekends	11.11
Once a week	37.04
3–5 times a week	19.05
Every day	2.12
Years drinking wine	13.74 (12.20)
# of subjects	189
# of bids = $0.00	137

https://doi.org/10.1017/age.2023.11 Published online by Cambridge University Press

Table 6. Tobit estimation results, tasting choice, and WTP for wine

	(1) bid	(2) bid	(3) bid	(4) bid
bid				
tasted	4.171***	4.115***	4.088***	4.186***
	(0.602)	(0.610)	(0.574)	(0.572)
Controls	None	Bottle fixed effects	Bottle fixed effects, age, gender, education, and race	Bottle fixed effects, age, gender, education, race, wine consumption habits, and wine knowledge
N	1134	1134	1116	1116
Left-censored	137	137	132	132
Clusters for errors	189	189	186	186
Pseudo R-squared	0.00872	0.00996	0.0234	0.0264
Log-likelihood	−3697.2	−3692.5	−3590.1	−3579.1
p-Value for model test	7.09e-12	1.73e-14	6.52e-73	2.83e-72

Standard errors are in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

estimation results for different specifications are provided in Table 6. The results are consistent and on average selecting a wine for tasting is associated with an approximately $4 higher consumer WTP. Specifications 1–4 differ on the number of controls included; as some of the gender and income data are not reported by five respondents, their bids were omitted from the estimation.

H3. Positive expert and peer information increases consumer WTP for wine, while negative peer and expert information reduces consumer WTP for wine.

Study 2 allows us to evaluate the impact of latent peer preference cues on consumer own WTP valuation for the wines available in the study. Compared to study 1, we are able to see the impact of peer information for both tasted wines and wines that have not been tasted. Previous research suggests that in absence of direct experience with a product, consumers might rely more on external cues (Chung and Saini 2022), which would increase the importance of peer influences on wines that have not been tasted. On the other hand, consumers prefer the wines that they select for tasting and might not care about peer preferences for options they do not personally consider attractive. We test the potential for such behavior with a series of Tobit model estimations, with results presented in Table 7. We use a continuous interaction of the level of tasting by peers observed for each wine in a session by the dummy variable indicating whether that wine has been tasted by the participant or not. As the decision of others to taste a wine is independent from your own decision to taste it by design, it removes the endogeneity problem and allows for causal identification of the impact of peer popularity on consumer WTP.

We use two approaches to measure peer popularity. One measures the proportion (in percentage terms) of people in each experimental session, not including the participant

Table 7. Tobit estimation results, impact of tasting popularity, measured as percentage of peers tasting the wine, on consumer WTP

	(1) bid	(2) bid	(3) bid	(4) bid
0.tasted# popularity	−0.0194**	−0.0212**	−0.0163*	−0.0174**
	(0.00978)	(0.00962)	(0.00906)	(0.00883)
1.tasted# popularity	0.0423***	0.0409***	0.0452***	0.0456***
	(0.0103)	(0.0111)	(0.0101)	(0.00989)
Controls	None	Bottle fixed effects	Bottle fixed effects, age, gender, and education, race	Bottle fixed effects, age, gender, education, race, wine consumption habits, and wine knowledge
N	1122	1122	1104	1104
Left-censored	137	137	132	132
Clusters for errors	187	187	184	184
Pseudo R-squared	0.00652	0.00800	0.0212	0.0231
Log-likelihood	−3658.1	−3652.7	−3551.7	−3544.9
p-Value for model test	3.01e-08	1.79e-10	4.70e-71	1.21e-69

Standard errors are in parentheses.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

themselves, who have tasted a given wine. Alternatively, we use the total number of people in the session, not including the respondent themselves, tasting that wine. The second measure ignores differences in the number of people present in the experimental session. Both measures vary for each person for each of the six bottles used in the experiment. Results are presented in Tables 7 and 8.

The estimation results are consistent between the two approaches to measuring peer popularity and between specifications with various levels of controls. The difference in scale of the coefficient has to do with the differences in the interpretation of Tobit coefficients. In Table 8, seeing one more person tasting a wine bottle leads to a 59-cent reduction in WTP for wine consumers who did not taste and an almost $1 increase in WTP for wine consumers who tasted themselves. In Table 7, an increase in the observed wine popularity of 1%, so having 1% more people tasting it leads to an approximately 2-cent reduction in consumer WTP for not tasted wine and an approximately 4-cent increase for tasted wine. As most of our tasting sessions only provided four peer-choice observations for each wine, a change in one person can be estimated as a change of around 25%. With that adjustment results in Table 7 are comparable with Table 8, with 25% change in popularity during tasting leading to a 30-cent and a 1-dollar change for non-tasted and tasted wines, respectively.

While the results for wines that have not been tasted are less significant (most of them only significant at the 10% level), the asymmetric nature of the peer popularity for preferred and less preferred wines, as measured by consumer decision to taste, is very interesting. This finding provides indirect support to our hypothesis on the impacts of congruency between external and internal evaluations.

Table 8. Tobit estimation results, impact of tasting popularity, measured as number of peers tasting the wine, on consumer WTP

	(1) bid	(2) bid	(3) bid	(4) bid
0.tasted# popularity	−0.698**	−0.743**	−0.638**	−0.590*
	(0.345)	(0.348)	(0.317)	(0.312)
1.tasted# popularity	0.841***	0.794**	0.890***	0.946***
	(0.320)	(0.346)	(0.309)	(0.299)
Controls	None	Bottle fixed effects	Bottle fixed effects, age, gender, education, and race	Bottle fixed effects, age, gender, education, race, wine consumption habits, and wine knowledge
N	1134	1134	1116	1116
Left-censored	137	137	132	132
Clusters for errors	189	189	186	186
Pseudo R-squared	0.00617	0.00761	0.0211	0.0237
Log-likelihood	−3706.7	−3701.3	−3598.9	−3589.1
p-Value for model test	0.000000221	2.61e-10	2.25e-71	1.07e-70

Standard errors are in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

H5. Peer and expert information congruent with consumer own evaluation of wine have a differential impact on consumer WTP.

For ease of exposition, we provide the estimates of the impact of wine popularity for tasted and non-tasted wines in Fig. 2, for both popularity measures. Overall, the pattern is very consistent, with peer popularity increasing consumer WTP for wines they have tasted, but somewhat reducing it for wines they did not pick for tasting. In other words, when peer popularity is congruent with their own preferences for wine, consumers increase their WTP; however, incongruent popularity leads to a decrease in WTP. Moreover, the impact of congruent peer rating has a larger impact than the comparative incongruent peer rating.

Discussion

Reviews and third-party quality valuation information is becoming more and more accessible for a variety of consumer products through easy online searches, databases, and social-based apps (Chen and Xie 2008). The question of how information about peer preferences and expert reviews impacts consumer behavior around products that consumers are able to sample themselves has remained underexplored.

Using two experimental studies in a wine tasting setting, we investigate the impact of peer preferences and experts' evaluations on consumer demand for wines that they have tasted, and, in case of peer information, for those they opted not to taste. We find that when consumers are able to taste the wines, their own rating of wine has the strongest

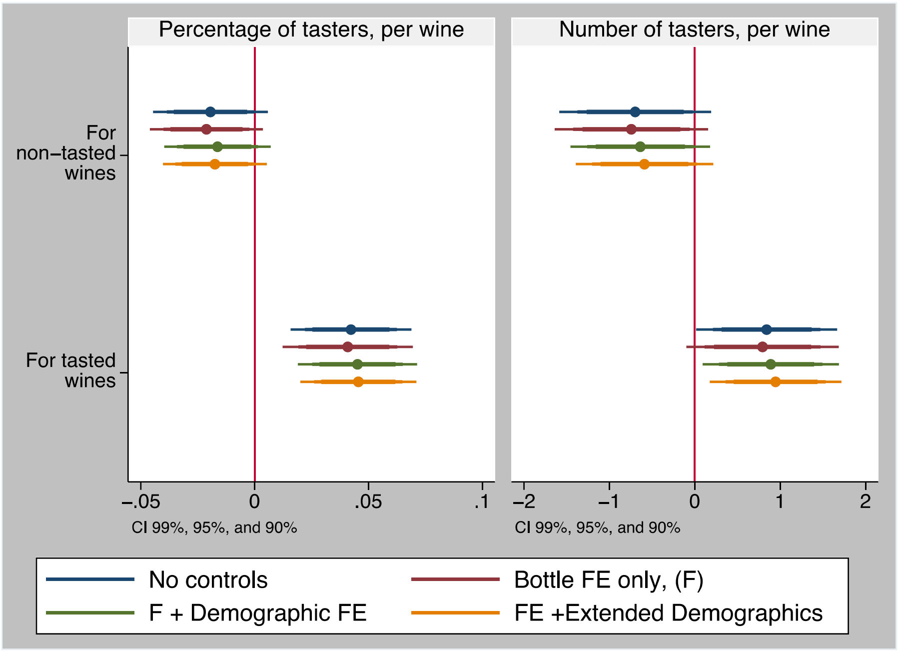

Figure 2. Coefficient estimate plot, Tobit estimation, wine popularity, with confidence intervals.

impact on their WTP, with one star (out of five possible) higher rating associated with an approximately $3 increase in WTP for wine. Similarly, in study 2, consumers are willing to pay significantly more for wines they choose for tasting, compared to the ones they do not.

The impact of peer and expert information, however, remains significant even after controlling for own ratings: we estimate that a one-star increase in peer and expert ratings still leads to an approximately $1.96 and $1.15 higher WTP, respectively. Contrary to existing research (Buonanno et al. 2010; Flanagin and Metzger 2013), we find little difference in consumer reaction to peer and expert information. It is possible that participants are less likely to identify peer evaluation of wine as important to their decision-making ex ante, especially for wines already tasted, as this might be interpreted as being too dependent on other people's opinions and looking for external approval. In this case, some of the studies that compared peer and expert recommendations impact on consumer behavior might underestimate peer impact, if relying on participant-reported relative importance of the two sources of information. As we observe the direct impact of provided peer information on participant WTP for wine, our estimates do not rely on consumer introspection or self-reporting.

We find more nuanced results when tasting choice is not independent of consumer preferences. We find that for wines consumers preferred to taste, higher peer popularity, which is independent of consumer's own preference for the wine, leads to a significant increase in consumer WTP. The opposite is true for wines not selected for tasting: higher popularity leads to lower WTP. This is an intriguing asymmetry in consumer interpretation of peer popularity information when the consumption or tasting choice has been made before the peer popularity is observed. It is in line with research on review congruence and confirmation bias (Buonanno et al. 2010; Flanagin and Metzger 2013; Cardebat and Livat 2016; Zaleskiewicz and Gasiorowska 2018): when peers like wines preferred by consumers, this confirms own evaluation and positively affects consumer WTP; when peers like wines not preferred by the consumers, this peer information can be disregarded, particularly when the difference between own opinion and peer popularity is large. In other words, consumers can be mentally defending their choice, by rejecting information in conflict with their preference, but appreciating the positive signals supporting their choice (Metzger et al. 2010). Our study, however, does not allow us to explicitly identify the reasons behind observed behavior, and more research is required to provide better understanding of consumer behavior.

Moreover, moving beyond situations where consumers make an explicit tasting choice before observing peer popularity, the results on rating congruency are mixed. The impacts of differences in consumer's own and peer or expert ratings mostly do not change with the scale of the differences. Specifically, in study 1, we find that reactions to peer rating information might vary more between different respondents, while the impact of expert information might be more consistent. Overall, reliance on noisy information signals and absence of full tasting information for all wines might make confirmation bias more pronounced (Zaleskiewicz and Gasiorowska 2018).

Finally, we do not find that providing expert or peer information "grows the size of the pie" by shifting demand; rather information provision allows for a better match between participants' own preferences and the characteristics of the wine, rotating the demand curve for individual wines. This is particularly pertinent for wineries deciding on their information provision policy for the whole list of wines available for tasting or purchase, as rating information provision is unlikely to generate more demand for less preferred options, but might affect particular wine shares of purchases made. While our results are indicative of this in the tasting setup, more support for stakeholder decision-making can be provided by explicitly investigating the impact of peer rating on consumer propensity to buy in future research.

Conclusion

Our results are relevant to brand managers and marketing professionals who use both product sampling or tasting, and expert or peer preference information in their materials. Overall, our results suggest that providing positive information for wines consumers have tasted and are interested in is worthwhile, as it can significantly further increase consumer WTP for any given option. As no significant difference between peer and expert information is observed, either type can be used in promotion depending on their relative positivity, potentially reducing pressure on obtaining costly and precise expert ratings.

In brick-and-mortar stores, peer rating or popularity information provision is, in the experience of the authors, quite rare. However, one can often observe high Wine Spectator or other expert-sourced ratings listed on the bottles, or next to them. This is particularly interesting given the relatively higher cost of obtaining positive expert ratings compared to positive consumer testimonials or evaluations. Our research suggests that positive peer valuation signals can play a significant role in marketing products, with or without expert reviews. However, we find that for reversing negative personal evaluation of a product, the focus should be on positive expert evaluations, as peer signals are more likely to be interpreted through the prism of confirmation bias.

While our results provide a first approach evaluation of consumer behavior in presence of tasting and external rating information, they rely on data collected in experimental lab settings. More research should be carried out to estimate the scale of impacts and their relative importance in field settings, where more information and environmental cues are vying for consumer attention. Our studies have focused on wine, a peculiar consumer good with some cultural and reputational weight. Such products might be more or less susceptible to influence of peer and expert valuations, and our results might differ in their magnitude for products less likely to be shared or interpreted as a social signal. Future research should extend the examination to other food and agricultural products, as well as other consumer goods.

Data availability statement. The anonymized data and code will be made available for replication purposes. The study has been approved under FLEX designation by the Oregon State University Institutional Review Board.

Funding statement. This research was supported by the Oregon Wine Board research grant (no grant number available).

Competing interests. Authors Nadeeka Weerasekara and Nadia Streletskaya declare none.

References

Alemu, M.H., and S.B. Olsen. 2020. "An Analysis of the Impacts of Tasting Experience and Peer Effects on Consumers' Willingness to Pay for Novel Foods." *Agribusiness* **36**(4): 653–674.

Alonso, A.D., L. Sheridan, and P. Scherrer. 2008. "Importance of Tasting Rooms for Canary Islands' Wineries." *British Food Journal* **110**(10): 977–988.

Aqueveque, C. 2015. "The influence of experts' positive word-of-mouth on a wine's perceived quality and value: the moderator role of consumers' expertise." *Journal of Wine Research* **26**(3): 181–191.

Aqueveque, C. 2018. "Ignorant Experts and Erudite Novices: Exploring the Dunning-Kruger Effect in Wine Consumers." *Food Quality and Preference* **65**: 181–184.

Azrieli, Y., C.P. Chambers, and P.J. Healy. 2018. "Incentives in Experiments: A Theoretical Analysis." *Journal of Political Economy* **126**(4): 1472–1503.

Bearden, W.O., and M.J. Etzel. 1982. "Reference Group Influence on Product and Brand Purchase Decisions." *Journal of Consumer Research* **9**(2): 183–194.

Becker, G.M., M.H. DeGroot, and J. Marschak. 1964. "Measuring Utility by a Single-Response Sequential Method." *Behavioral Science* **9**(3): 226–232.

Benjamin, B.A., and J.M. Podolny. 1999. "Status, Quality, and Social Order in the California Wine Industry." *Administrative Science Quarterly* **44**(3): 563–589.

Buonanno, P., G. Caggiano, M.M. Galizzi, L. Leonida, and P. Vanin. 2010. "Expert and Peer Pressure in Food and Wine Tasting: Evidence from a Pilot Experiment." *Enometrica* **1**: 51–68.

Burnkrant, R.E., and A. Cousineau. 1975. "Informational and Normative Social Influence in Buyer Behavior." *Journal of Consumer Research* **2**(3): 206–215.

Cardebat, J.-M., and F. Livat. 2016. "Wine Experts 'Rating: A Matter of Taste?" *International Journal of Wine Business Research* **28**(1): 43–58.

Chakraborty, U., and S. Bhat. 2018. "The Effects of Credible Online Reviews on Brand Equity Dimensions and Its Consequence on Consumer Behavior." *Journal of Promotion Management* **24**(1): 57–82.

Chen, Y., and J. Xie. 2008. "Online Consumer Review: Word-of-Mouth as a New Element of Marketing Communication Mix." *Management Science* **54**(3): 477–491.

Childers, T.L., and A.R. Rao. 1992. "The Influence of Familial and Peer-Based Reference Groups on Consumer Decisions." *Journal of Consumer Research* **19**(2): 198–211.

Chung, M., and R. Saini. 2022. "Consumer Self-Uncertainty Increases Price Dependency." *Journal of Business Research* **140**: 40–48.

Cuellar, S.S., and M. Claps. 2013. "Differential Effects of Brand, Ratings and Region on Willingness to Pay: A Hedonic Price Approach." *Journal of Wine Research* **24**(2): 138–155.

Erdem, T., and M.P. Keane. 1996. "Decision-Making under Uncertainty: Capturing Dynamic Brand Choice Processes in Turbulent Consumer Goods Markets." *Marketing Science* **15**(1): 1–20.

Flanagin, A.J., and M.J. Metzger. 2013. "Trusting Expert- versus User-Generated Ratings Online: The Role If information Volume, Valence, and Consumer Characteristics." *Computers in Human Behavior* **29**(4): 1626–1634.

Fountain, J., N. Fish, and S. Charters. 2008. "Making a Connection: Tasting Rooms and Brand Loyalty." *International Journal of Wine Business Research* **20**(1): 8–21.

Friberg, R., and E. Grönqvist. 2012. "Do Expert Reviews Affect the Demand for Wine?" *American Economic Journal: Applied Economics* **4**(1): 193–211.

Griskevicius, V., J.M. Tybur, and B. Van den Bergh. 2010. "Going Green to be Seen: Status, Reputation, and Conspicuous Conservation." *Journal of Personality and Social Psychology* **98**(3): 392.

Heiman, A., B. McWilliams, Z. Shen, and D. Zilberman. 2001. "Learning and Forgetting: Modeling Optimal Product Sampling Over Time." *Management Science* **47**(4): 532–546.

Jain, D., V. Mahajan, and E. Muller. 1995. "An Approach for Determining Optimal Product Sampling for the Diffusion of a New Product." *Journal of Product Innovation Management* **12**(2): 124–135.

Johnson, J.P., and D.P. Myatt. 2006. "On the Simple Economics of Advertising, Marketing, and Product Design." *American Economic Review* **96**(3): 756–784.

Kolyesnikova, N., and T.H. Dodd. 2009. "There Is No Such Thing as a Free Wine Tasting: The Effect of a Tasting Fee on Obligation to Buy." *Journal of Travel & Tourism Marketing* **26**(8): 806–819.

Lammers, H.B. 1991. "The Effect of Free Samples on Immediate Consumer Purchase." *Journal of Consumer Marketing* **8**(2): 31–37.

Liaukonyte, J., N.A. Streletskaya, and H.M. Kaiser. 2015. "Noisy Information Signals and Endogenous Preferences for Labeled Attributes." *Journal of Agricultural and Resource Economics* **40**(2): 179–202.

Lynch Jr J.G., and D. Ariely. 2000. "Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution." *Marketing Science* **19**(1): 83–103.

Marks, D. 2015. "Seeking the Veritas About the Vino: Fine Wine Ratings as Wine Knowledge." *Journal of Wine Research* **26**(4): 319–335.

McCole, D., D. Holecek, C. Miller-Eustice, and J.S. Lee. 2018. "Wine Tourists in Emerging Wine Regions: A Study of Tasting Room Visitors in the Great Lakes Region of the US. *Tourism Review International* **22**(2): 153–168.

Metzger, M.J., A.J. Flanagin, and R.B. Medders. 2010. "Social and Heuristic Approaches to Credibility Evaluation Online." *Journal of Communication* **60**(3): 413–439.

Munnukka, J., O. Uusitalo, and H. Toivonen. 2016. "Credibility of a Peer Endorser and Advertising Effectiveness." *Journal of Consumer Marketing* **33**(3): 182–192.

Neuninger, R., D. Mather, and T. Duncan. 2017. "Consumer's scepticism of wine awards: A Study of Consumers' Use of Wine Awards." *Journal of Retailing and Consumer Services* **35**: 98–105.

Oczkowski, E., and H. Doucouliagos. 2015. "Wine Prices and Quality Ratings: A Meta-Regression Analysis." *American Journal of Agricultural Economics* **97**(1): 103–121.

Reinstein, D.A., and C.M. Snyder. 2005. "The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics." *The Journal of Industrial Economics* **53**(1): 27–51.

Smith, D., S. Menon, and K. Sivakumar. 2005. "Online Peer and Editorial Recommendations, Trust, and Choice in Virtual Markets." *Journal of Interactive Marketing* **19**(3): 15–37.

Stiletto, A., E. Rozzanigo, E. Giampietri, and S. Trestini. 2021. "Taste Beats Reputation in New Food Products Choice: The Case of Ready-to-Eat Pomegranate among Young Consumers in Veneto Region (Italy)." *Horticulturae* **7**(7): 179.

Streletskaya, N.A. 2022. "Evaluating the Impact of Strangers on Shopping Behavior through Video and Sales Data. *Working Paper*.

Streletskaya, N.A., J. Liaukonyte, and H.M. Kaiser. 2019. "Absence Labels: How Does Information about Production Practices Impact Consumer Demand?" *PloS One* **14**(6): e0217934.

Thrane, C. 2019. "Expert Reviews, Peer Recommendations and Buying Red Wine: Experimental Evidence." *Journal of Wine Research* **30**(2): 166–177.

Wine Spectator. 2021. "Wine Spectator.com Ratings Beta Search." Available at: https://www.winespectator.com/wines/searchv2 (accessed February 22, 2022).

Wu, X., L. Jin, and Q. Xu. 2021. "Expertise Makes Perfect: How the Variance of a Reviewer's Historical Ratings Influences the Persuasiveness of Online Reviews." *Journal of Retailing* **97**(2): 238–250.

Zaleskiewicz, T., and A. Gasiorowska. 2018. "Tell Me What I Wanted to Hear: Confirmation Effect in Lay Evaluations of Financial Expert Authority." *Applied Psychology* **67**(4): 686–722.

Zhu, J., D.K.C. Tse, and Q. Fei. 2018. "Effects of Online Consumer Reviews on Firm-Based and Expert-Based Communications." *Journal of Research in Interactive Marketing* **12**(1): 45–78.

Cite this article: Weerasekara, N. and N. A. Streletskaya (2024). "Tasting and consumer demand for wine: do peers and experts matter?" *Agricultural and Resource Economics Review* **53**, 66–86. https://doi.org/10.1017/age.2023.11