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ARTICLE

Factors influencing wine ratings in an online wine community: The case of Trentino–Alto Adige

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Abstract

Consumers often struggle to make their choice in the highly diversified wine market. With wine being an experience good, consumers must rely on extrinsic characteristics, e.g., information on the label. Thus, easily available quality signals like consumer ratings have become an increasingly useful and widespread tool. Vivino is one of the largest online wine communities with over 60 million users, which have more than doubled since 2018. Hence, users have easy access to peer ratings, while established wine expert ratings are being challenged. This study analyzes data from Vivino to explore factors affecting consumer ratings at different price points, considering several wine attributes like geographical indications, brand, and the so-called "community effect." We show that there is a small but significant community effect on wine's perceived quality related to its popularity among users of the Vivino community, as well as effects from specific wine attributes. Moreover, we estimate a hedonic quantile model on similar price ranges to compare the effect of the same regressors on wine prices. Results contribute to a better understanding of how different factors affect consumers' wine evaluations, allowing to compare their effect on the "pure" consumer preference (i.e., consumer ratings) and market value.

Keywords: consumer ratings; wine; price; Italy; hedonic quantile regression (HQR)

JEL classifications: C21; Q11; D12.

I. Introduction

Wine is a highly differentiated product in the agri-food sector due to the strong links between quality, varieties, vintages, regions of origin (Charters and Pettigrew, 2007), and the corresponding price variations (Chandra and Moschini, 2022). In such diverse markets, consumers face difficulties in fully evaluating product quality (Akerlof, 1970). For wine, it is widely acknowledged that consumers use certain extrinsic features on wine labels, such as country and/or region of origin, grape variety, brand, and price, to evaluate product quality (Jaeger et al., 2013; Lockshin and Corsi, 2012;

Mueller and Szolnoki, 2010; Sáenz-Navajas et al., 2013). However, the general inability to taste wine prior to purchasing means that consumers are forced to rely on imperfect information when evaluating quality. Consumers often rely on sensory quality assessments, including expert ratings, awards, competition results, and tasting notes, to bridge the information gap (Ribeiro et al., 2020).

The literature on the impact of expert ratings on the wine market is extensive, and many studies emphasize the influence of such ratings on consumer willingness to pay (Neuninger et al., 2016; Schäufele et al., 2016), wine selection (Goodman, 2009; Lockshin et al., 2006), and regional or winery reputation (Penagos-Londoño et al., 2023). Expert ratings drive wineries' success by influencing consumer sales and prices. Multiple studies support this claim (Oczkowski and Doucouliagos, 2015; Schamel and Anderson, 2003; Schamel and Ros, 2021), at least for high-rated "superstar" wines (Castriota et al., 2022). Demand for highly rated wines among wine producers has increased, causing an inflation of prices (Kotonya et al., 2018). Considering this, significant scrutiny has arisen regarding the validity of expert wine ratings as sensory evaluations are profoundly subjective, reflecting the taste preferences of just one individual (Oczkowski and Pawsey, 2019).

Consumers, on the other hand, have easy access to the opinions of their peers and have become increasingly active in rating and reviewing wines. Thus, they no longer need to rely only on individual wine experts. Anderson and Magrunder (2012) highlighted the importance of consumer opinions and social learning in shaping product beliefs and, hence, purchase decisions for experiential goods such as wine. With the rapid growth of online communities and marketplaces (e.g., Vivino and Cellartracker), ordinary consumers can share their wine experience and knowledge through reviews and ratings. Consumer opinions and aggregated wine ratings are accessible to peer users. For example, Vivino, the world's most downloaded wine app, which has developed into an online marketplace, claims that you can "check out honest reviews … add your rating and help other Vivino users choose the right wine!" When consumers use aggregated ratings from their peers, a form of social influence occurs, i.e., people are influenced by group behavior and tend to comply and conform (see Cialdini and Goldstein, 2004 for a review). Therefore, online consumer ratings and reviews can play a crucial role in promoting brand loyalty and have a notable influence on consumers' purchase decisions (Gavilan et al., 2018).

Average ratings in a five-star rating system are easily accessible information cues that facilitate consumers' information processing and reduce cognitive effort while providing high information quality (Chen, 2017). In addition to average ratings, the number of ratings and reviews a product receives is important for online purchases. The number of reviews provides social proof and generates trust (Gavilan et al., 2018; Lee et al., 2011). It is interesting to note that average rating scores interact with the number of reviews. One might assume that a high number of reviews would make an average review score a reliable number. However, Gavilan et al. (2018) and Hong and Pittman (2020) found that this is only true for "good" ratings.

Consumer ratings for hotels (see Hu and Yang, 2021 for a meta-analysis), restaurants (Bilgihan et al., 2018; Tian et al., 2021; Yan et al., 2015), or review websites, such as Amazon and Yelp (see Floyd et al., 2014 and Hong et al., 2017 for a meta-analysis), have already gained a lot of interest in the scientific literature. Instead, research on consumer ratings on wine platforms such as vivino.com or cellartracker.com is still developing (e.g., Kopsacheilis et al., 2023; Mazzoli and Palumbo, 2022).

Oczkowski and Pawsey (2019) found a gap between consumer and expert ratings and pointed to diverging sensory preferences. Moreover, their study provides evidence for a correlation between consumer ratings and wine prices. A common explanation given is the fact that consumers use prices as an indicator of quality, and according to this subconscious influence, higher-priced wines receive higher consumer ratings (Gokcekus and Nottebaum, 2011; Oczkowski and Pawsey, 2019). In contrast, the study by Kotonya (2018) gives little evidence for a strong relationship between prices and consumer ratings. Nevertheless, both Kotonya's (2018) and Oczkowski and Pawsey's (2019) results suggest that expert opinions and online wine community reviews are related and often comparable. Such results have also been confirmed by a recent market experiment run by U.S. wine critic Ester Mobley on Vivino users from California in 2022. Indeed, Mobley's wine evaluations turned out to be remarkably like those of app users except for high-priced luxury wines (above €200), which were indeed rated significantly higher on Vivino (Mobley, 2022). Similarly, Bazen et al.'s (2023) hedonic analysis of French wines on Vivino found community ratings to have a greater impact on wine price than experts, except for top-end wines.

Our study will add to the knowledge of online consumer ratings in two ways. First, we explore factors influencing consumer rating itself. A rating model will examine the so-called "community effect" or the impact of the number of ratings. Second, we study the effects of wine attributes on price to find out if there is a consistency between the factors affecting consumer ratings and those affecting prices. Thus, a hedonic price analysis with the same determinants as for the ratings model is carried out. Indeed, to the best of our knowledge, these aspects are still unexplored by the academic literature. Particularly, we formulated the following research questions (RQs):

RQ1: How do consumer ratings respond to the influence of the community effect while accounting for essential wine characteristics?

RQ2: What is the impact of wine attributes on wine prices and are those effects consistent with the factors affecting consumer ratings?

We expect that individual consumer ratings are influenced by how often a wine has been rated, i.e., the more popular a wine becomes among consumers (expressed by the number of ratings), the higher the wine will be rated. We control for both Geographical Indication (GI) and brand effects. The literature on GIs has shown that more restrictive GI rules lead on average to a greater perceived quality. Specifically, Protected Designation of Origin (PDO) tend to be valued more than Protected Geographical Indication (PGI) (Caracciolo and Furno, 2020). The wine brand literature has shown that the quality performance of co-op brands is generally lower relative to privately owned brands (Pennerstorfer and Weiss, 2013; Schamel, 2015) although exceptions may exist (Frick, 2017; Schamel, 2014).

Hedonic pricing models assume that wine price is a combination of implicit prices of wine attributes and thus reveal consumer preferences (Outreville and Le Fur, 2020). Wine price formation is the result of both consumer preferences (Ling and

Lockshin, 2003; Oczkowski and Doucouliagos, 2015) and production costs based on vintage, geographical origin, and certification. On the other hand, consumer preferences mostly reflect the evaluation of a wine and perceptions its attributes. Signals like observed product prices can affect such perceived value, leading to higher ratings (e.g., Almenberg and Dreber, 2011), but perceived values of single attributes may not necessarily correspond to estimated implicit prices. This may happen due to consumers' lack of knowledge and awareness of production and/or certification characteristics, as previous research has observed (e.g., Costanigro et al., 2019; Jover et al., 2004; Teuber, 2011).

II. Materials and methods

a. Dataset description

We obtained the data from Vivino.com, the main online wine community in Italy (Mastroberardino et al., 2020). Currently, it lists over 17 million wines from all over the world rated over 279 million times and is the world's most downloaded wine app, growing from about 27 million users in 2018 to 42 million in 2020 to over 66 million in 2023[1]. In April 2022, we collected 1,747 observations of vintage wines from Trentino–Alto Adige (TAA) with at least 25 ratings and a price quote, meaning that they were available directly from Vivino or through external online shops. For a vintage wine with less than 25 ratings, no unique rating is available but only an average over all vintages of the same wine. If the same wine has more than 25 ratings over several vintages, it may appear multiple times in the data. The price quotes are either directly from Vivino or average online prices from external shops.[2]

In the paper, we analyze wines from TAA in northern Italy, which is known for the strength of their cooperative wine producers (Schamel, 2014; Weinwirtschaft, 2022), with a volume share of about 70% (Raiffeisenverband, 2022). Combined, the two provinces produce 1.3 billion hectoliters of wine, 83.7% of which is PDO and 15.2% is PGI.[3] We have information on wine names (*wname*), producer brand names (*producer*), vintages (*vintage*), average ratings received from Vivino users (*rating*), the number of ratings for each vintage wine (*nratings*), the price per bottle (*price*), as well as wine attributes such as variety (*variety*), and the *GI* of the wine.

In Table 1, we summarize the descriptive statistics, including information on producer brands and if the wine is from a cooperative (co-op) or investor-owned firm (IOF). Note that producer brand information is highly fragmented: only 20 of 138 producer brands in the sample have 29 or more wines in the sample. Our sample identifies 44 distinct varieties and blends. The main varieties grown in Trentino (TN) and Alto Adige (AA) are Lagrein (2.1% TN/10% AA), Pinot Noir (3.5%/10%), Merlot (5.4%/3%), Schiava (2.3%/9%), Cabernets (2.4%/3%),[4] Pinot Grigio (29%/12%),

[1] https://www.vivino.com/about

[2] We checked the consistency of these prices and confirm that they are usually at the lower end of published online prices. Inconsistencies may exist for older vintages with limited availability still listed. We deal with this problem by excluding rare and older vintages with high prices from the analysis.

[3] The remaining 1.1% is table wine. ISTAT, 2022. https://www.istat.it

[4] Please note that in TAA, the varietal information usually does not distinguish between Cabernet Sauvignon, Cabernet Franc, and field-blends thereof. See https://vinideltrentino.com/en/trentinos-wines/ and https://www.altoadigewines.com/en/wine-varieties/wine-varieties/68-0.html

Table 1. Sample descriptive statistics

Categorical and ordinal variables	*n*	%		*n*	%
Geographical indication (GI)	1,747		*Producer brand*	1,747	
PDO	1,536	87.9	IOF Brand 1	79	4.52
PGI	211	12.1	Co-op Brand 2	79	4.52
Vintage	1,747		Co-op Brand 3	76	4.35
2015 or older	333	19.1	Co-op Brand 4	72	4.12
2016	146	8.4	Co-op Brand 5	69	3.95
2017	214	12.2	Co-op Brand 6	64	3.66
2018	331	19	IOF Brand 7	58	3.32
2019	367	21	Co-op Brand 8	58	3.32
2020–2021	323	18.5	Co-op Brand 9	56	3.21
No vintage (N.V.)	32	1.8	IOF Brand 10	52	2.98
Variety	1,747		Co-op Brand 11	47	2.69
Lagrein	210	12	Co-op Brand 12	46	2.63
Pinot Noir	197	11.3	IOF Brand 13	44	2.52
Chardonnay	144	8.2	IOF Brand 14	41	2.35
Pinot Blanc	136	7.8	Co-op Brand 15	38	2.18
Sauvignon Blanc	136	7.8	IOF Brand 16	35	2
Gewürztraminer	128	7.3	IOF Brand 17	34	1.95
Pinot Grigio	102	5.8	Co-op Brand 18	32	1.83
Schiava	85	4.9	Co-op Brand 19	32	1.83
Teroldego	66	3.8	IOF Brand 20	29	1.66
Merlot	60	3.4	Other	706	40.41
Müller Thurgau	47	2.7	*Co-op wines*	1,747	
Cabernets	47	2.7	1 (Yes)	788	45.1
Other varietals	180	10.3	0 (No)	959	54.9
Red/rosé blend	117	6.7	*Price ranges*	1,747	
White blend	92	5.3	price $\leq$ €12.5/bottle	450	25.8
			€12.5 $<$ price $\leq$ €26/bottle	855	48.9
			price $>$ €26/bottle	442	25.3

Continuous variables	n	Mean	Std. dev.	Min	Max
Number of ratings (nratings)	1,747	197.3	641.8	25	22352
Rating	1,747	3.9	0.25	2.8	4.7
Price (€/bottle)	1,747	23.4	22.84	4	280

Gewürztraminer (4%/11%), Pinot Blanc (0.7%/10%), Chardonnay (27%/11%), Sauvignon Blanc (1.2%/8%), and Müller-Thurgau (9.3%/3%). Teroldego (6.3%) is only grown in Trentino. Together, these varieties account for about 75% of the sample (Table 1). Regarding GIs, most wines are PDO, with a notable percentage from Alto

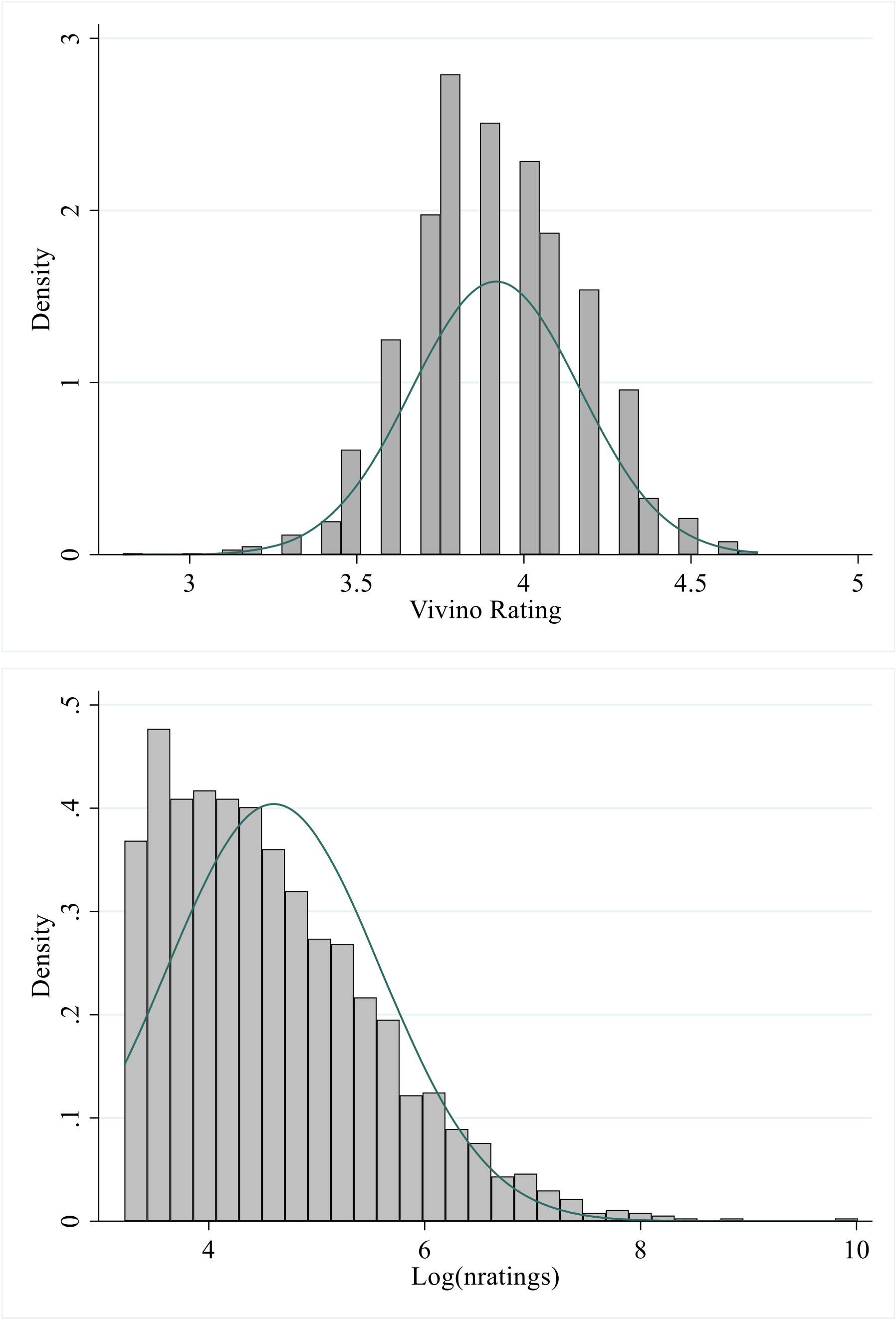

Figure 1. Distribution of *rating* and *nratings.*

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Adige PDO (roughly 70%), and 11% are PGI wines from the Vigneti delle Dolomiti. Vintages declared on the label range from 2003 to 2021, with 80% of them from 2010 to 2019.

Wine prices in €/bottle (*price*) reveal great variations across the sample and a highly skewed distribution, ranging from a minimum of €4.1/bottle to a maximum of €280/bottle (*price* mean = 23.4; std. dev. = 22.89). The *price* distribution is plausibly connected to the presence of champagne-style sparkling wines and aged reds. The *rating* variable has a close-to-normal but slightly kurtotic distribution (Figure 1, top). The mean rating is 3.92 (with a low std. dev. = 0.25), which is much higher than the 3.6 average for all wines reported on Vivino (Vivino, 2020). The *nratings* variable has a mean of 197.3 (with a high std. dev. = 642.8) and mainly reflects how popular the wine is among Vivino users. While it may also be related to how much of it was produced (rarity) and for how long it has been listed on the platform (recency), the lure to taste and rate rare wines and the growing number of users should counteract any negative bias caused by the rarity and recency of vintages.

In Figure 2, we graph the average Vivino rating against the quantiles of *nratings* represented as log(*nratings*). Interestingly, the average Vivino rating tends to gradually increase as wines are reviewed by more users, and there is also less variability in the ratings assigned. This observation suggests that, on average, wines that are popular among platform users (having more ratings) tend to get slightly higher ratings. Moreover, it indicates that as the wine accumulates an increasing number of reviews, new ratings are less likely to deviate from the crowd's opinion.

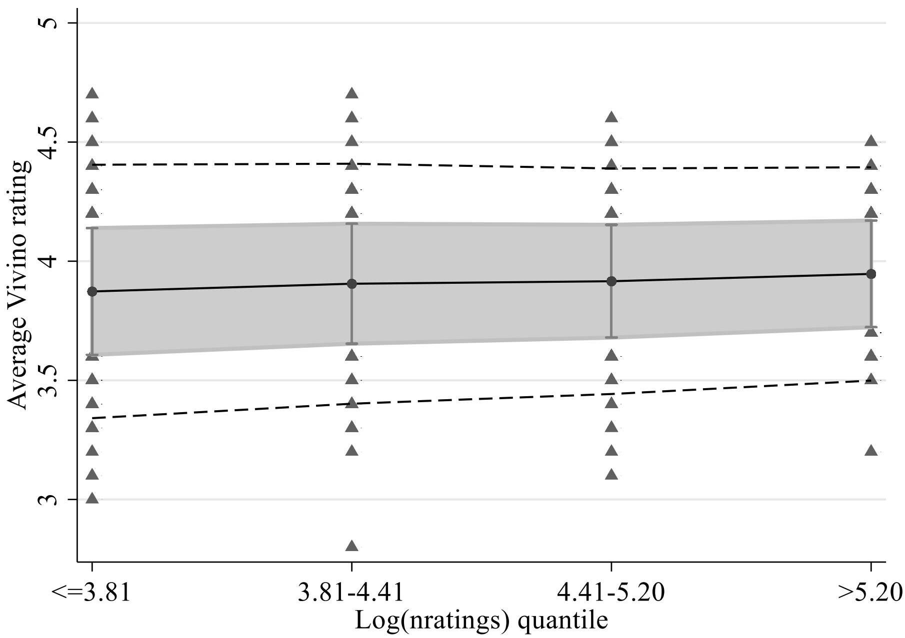

Figure 2. Average Vivino rating and standard deviation for each quantile of log(nratings).

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b. Empirical models specification

To address RQ1, given the remarkable price differentiation in the wine market (Costanigro et al., 2007), we estimate regression models with the Vivino rating as the dependent variable (DV) for three distinct price ranges. Price ranges are retrieved from quantiles of the *price-per-bottle* distribution at 25% (€12.5/bottle or lower; model 1), 50–75% (from €12.5 to €26/bottle; model 2), and above 75% (and above €26/bottle; model 3; see *priceord* in Table 1). The latter quantile is truncated at €100/bottle. Hence, we exclude a very small share of expensive wines in our sample (24 out of 1,747), which, based on existing knowledge (e.g., Gonen et al., 2021; Mobley, 2022), should be treated separately. Thus, 1,723 observations are eligible for the analysis.

We use the information on the number of ratings, grape variety, GI, vintage, and producer brands as regressors. As previously specified, the original variable *rating* is continuous and is expressed on a scale from 1 to 5. Since the distribution of *nratings* is not normal, the variable was logged. Varietal effects are captured by a categorical dummy variable. We control for and collinearity effect from blends by including two dummy variables for white wine blends (*white blend*) and red/rosé wine blends (*red/rosé blend*). Since GIs strongly correlate with grape varieties causing collinearity issues, the GI information is aggregated. The wines in our sample are either PDO (mostly Alto Adige DOC) or PGI (*Vigneti delle Dolomiti* IGT). Hence, we include a dummy variable, *PDO,* being 1 for PDO and 0 for PGI (Table 1).

The 2020/21 vintage and the 2015 and older vintages (selected as reference categories) and their respective dummies refer to multiple *vintages* because they have relatively few observations. Controlling for single producers was not possible due to the sample fragmentation. Thus, we include 20 producer brands with more than 29 wines (*brand30*), aggregating all others together as the reference category.

We thus estimate the regression models shown in equation (1) with the Vivino rating as the DV and the regressors as discussed for three price quantiles (Wooldridge, 2015):

$$
\begin{aligned}
lograting_{price\ range\ i} = {} & \beta_0 + \beta_1 lognrat + \sum_{n=1}^{5} \beta_2 V_{vintage} + \sum_{e=1}^{14} \beta_3 J_{variety} \\
& + \beta_4 PDO + \sum_{f=1}^{20} \beta_5 P_{brand\ 30} + \varepsilon_i \qquad (1)
\end{aligned}
$$

V and J are vectors of marginal effects due to specific vintages and grape varieties, respectively. Similarly, P is a vector including indicators for producer brands having 30 or more wines in the sample. White's test was conducted to detect heteroscedasticity (Wooldridge, 2015). In the case of a significant White test result, robust estimation was applied to handle heteroscedasticity. Furthermore, we run the Ramsey RESET test to detect model specification issues and calculate the variance inflation factor (VIF) to check for multicollinearity (Hair et al., 2019). Finally, endogeneity was assessed using the Hausman specification test. A significant coefficient for the residuals in the Hausman test indicates endogeneity.

To tackle RQ2, following Caracciolo et al. (2016) and Fedoseev et al. (2022), we estimate a hedonic quantile model (HQM) through conditional quantile regression shown in equation (2), as implicit prices vary significantly over different market price percentiles. This technique is widely used for robust estimations. It allows assessing the impact of the regressors on a specific quantile of *y* distribution, conditional to the value of the regressors in the model. Being a one-stage HQM, we restrict variables to wine-related features without incorporating producer-specific factors such as the reputation of the producer or quantity sold, as recommended by Oczkowski (2022). Specifically, we used the Stata *sqreg* function with 1,000 bootstraps to simultaneously estimate four quantiles of the *price* distribution: 25% (q25), 50% (q50), 75% (q75), and 90% (q90). The selected quantiles reflect the price ranges considered for the linear regressions on ratings. As in the study by Fedoseev et al. (2022), the DV was the logarithm of the price-per-bottle of each wine, and the same pool of regressors included in the rating regression models was used except for *lognrat*.

$$logprice_i = \beta_0 + \sum_{n=1}^{5} \beta_1 V_{vintage} + \sum_{e=1}^{14} \beta_2 J_{variety} + \beta_3 PDO + \sum_{f=1}^{20} \beta_4 P_{brand\,30} + \varepsilon_i \quad (2)$$

We exclude information on consumer ratings from this model (*rating* and *nratings*) since the current dataset considers the aggregated average rating a wine receives after its listing on Vivino until data collection and the prices at the time of data collection (April 2022). Therefore, a dynamic analysis of prices as consumer ratings change is not possible. Moreover, wine prices and quality perception are closely connected

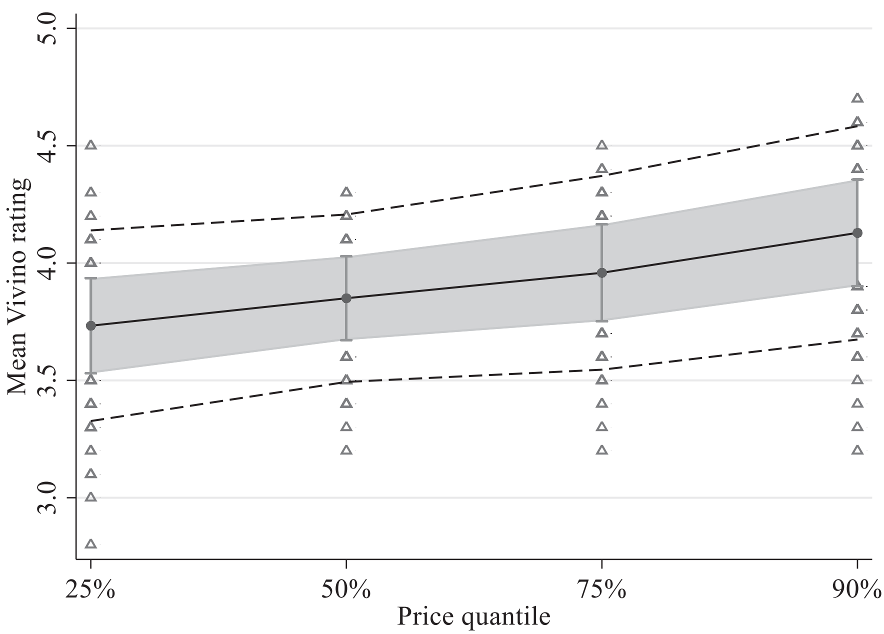

Figure 3. Mean rating and standard deviation by price quantile.

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(Priilaid and Hall, 2016), and Vivino users usually know the price when rating a wine. Figure 3 supports this relationship, showing how the average consumer rating increases as more expensive wines are considered. Thus, potential reverse causality effects can arise when trying to explain wine prices through consumers' ratings on Vivino.

Homogeneity among quantile coefficients was tested with the null hypothesis (H_0) being q(25) = q(50) = q(75) = q(90): statistically significant *p*-values at 5% indicate that the null hypothesis is rejected and that coefficients significantly differ among the estimated quantiles. Lastly, price effects in % are calculated for the categorical regressors based on Halvorsen and Palmquist (1980) as $(e^{\beta} - 1) \times 100$, where β is the estimated regression coefficient for the regressor considered.

III. Results

a. Regression models on community ratings

Table 2 reports the regression results for equation (1) for the three price quantiles considered (DV = *lograting*). The R^2 value varies from 0.25 (second quantile) to 0.31 (first quantile). Ramsey's test is not significant for all models, indicating that there are no omitted variables. Similarly, the VIFs for all models are below the common critical threshold of 10 (Hair et al., 2019; Table 2), and the insignificant effect from the Hausman test indicates that no endogeneity is present. The number of ratings (*lognrat*) has a small but *positive* effect in model 1 and 2 (i.e., for wine priced below €12.5 and in the €12.5–€26 range), while its coefficient is insignificant in model 3 (i.e., for high-priced wines). Similarly, co-op branded wines tend to receive significantly lower ratings in model 1 but show better performances than private (IOF-branded) wines in model 2. No significant effect appears for more expensive wines. The PDO certification does not lead to significantly higher wine evaluations compared to PGI in any of the price ranges. Diversely, a vintage effect is present in all the models. As expected, newer vintages tend to collect increasingly higher ratings in models 1 and 2. On the contrary, older vintages are particularly appreciated in the middle and top price ranges (models 2 and 3).

Finally, different varieties show heterogeneous effects. Gewürztraminer is the most appreciated among Vivino users, receiving greater average ratings compared to other varieties in the middle price range (model 2). Pinot Noir, as well as the local varieties Schiava, Teroldego, and Müller Thurgau, tend to be consistently less appreciated. Moreover, other varieties show isolated negative effects at one price point (i.e., Lagrein, Chardonnay, Cabernets, and Merlot) or at the two distribution extremes (e.g., Pinot Blanc and Pinot Gris). Lastly, producer performance is remarkably diverse. No co-op brand received greater average ratings in the lowest price segment, where some even perform significantly worse (e.g., Co-op Brand 8), while one winery (IOF Brand 14) seems to outperform competitors. Nevertheless, many co-op branded bottles in the middle price range are strongly appreciated by the Vivino community, recording even greater ratings for high-priced bottles.

b. Hedonic quantile regression on price

Estimates of the HQR model regarding RQ2 are presented in Table 3, while Table 4 summarizes the estimated price effects in % and the results of the homogeneity test

Table 2. Regression models on consumer ratings for the three price ranges

	Price < €12.5	€12.5 < Price ≤ €26	€26 < Price ≤ €100
DV: Vivino rating	Model 1	Model 2	Model 3
log (number of ratings)	0.029***	0.015**	−0.001
	(−0.011)	(−0.007)	(−0.013)
PGI (PDO = 0; *reference*)	0	0	0
	(.)	(.)	(.)
PDO (1)	0.066	−0.022	0.029
	(−0.045)	(−0.028)	(−0.045)
2015 or older vintage (*reference*)	0	0	0
	(.)	(.)	(.)
2016	0.071	0.097***	0.022
	(−0.053)	(−0.029)	(−0.031)
2017	0.067	0.108***	0.088***
	(−0.061)	(−0.024)	(−0.029)
2018	0.083*	0.123***	0.071**
	(−0.043)	(−0.021)	(−0.030)
2019	0.128***	0.084***	0.044
	(−0.038)	(−0.022)	(−0.041)
2020–2021	0.177***	0.106***	−0.05
	(−0.037)	(−0.025)	(−0.067)
Other varietals (*reference*)	0	0	0
	(.)	(.)	(.)
Red/rosé blend	−0.027	0.004	−0.019
	(−0.084)	(−0.033)	(−0.054)
White blend	−0.071	−0.025	−0.034
	(−0.090)	(−0.038)	(−0.057)
Cabernets	−0.193**	0.025	0.033
	(−0.090)	(−0.046)	(−0.066)
Chardonnay	−0.179***	−0.046	−0.049
	(−0.042)	−0.034	−0.056
Gewürztraminer	0.017	0.095***	0.037
	(−0.043)	(−0.030)	(−0.058)
Lagrein	−0.124***	0.006	−0.04
	(−0.043)	(−0.027)	(−0.054)
Merlot	−0.264**	0.017	−0.049
	(−0.104)	(−0.042)	(−0.066)
Müller Thurgau	−0.132***	−0.131***	−0.076
	(−0.050)	(−0.044)	(−0.072)
Pinot Blanc	−0.128***	−0.026	−0.279***
	(−0.041)	(−0.030)	(−0.082)

(*Continued*)

Table 2. (*Continued.*)

	Price < €12.5	€12.5 < Price ≤ €26	€26 < Price ≤ €100
DV: Vivino rating	Model 1	Model 2	Model 3
Pinot Gris	−0.089**	−0.031	−0.210**
	(−0.041)	(−0.029)	(−0.099)
Pinot Noir	−0.255***	−0.127***	−0.172***
	(−0.074)	(−0.026)	(−0.052)
Sauvignon Blanc	−0.021	0.034	−0.061
	(−0.042)	(−0.026)	(−0.059)
Schiava	−0.248***	−0.155***	−0.628***
	(−0.045)	(−0.036)	(−0.215)
Teroldego	−0.258***	−0.117**	−0.069
	(−0.076)	(−0.049)	(−0.083)
Other producer brands (*reference*)	0	0	0
	(.)	(.)	(.)
IOF Brand 1	−0.048	−0.199***	−0.122**
	(−0.061)	(−0.032)	(−0.055)
Co-op Brand 2	−0.032	0.101***	0.102**
	(−0.032)	(−0.034)	(−0.049)
Co-op Brand 3	−0.008	0.081**	0.114*
	(−0.034)	(−0.033)	(−0.065)
Co-op Brand 4	−0.031	−0.033	−0.041
	(−0.031)	(−0.034)	(−0.068)
Co-op Brand 5	0.005	0.019	−0.065
	(−0.032)	(−0.029)	(−0.061)
Co-op Brand 6	0.02	−0.015	0.066
	(−0.039)	(−0.036)	(−0.072)
IOF Brand 7	0.025	−0.014	0.024
	(−0.044)	(−0.036)	(−0.047)
Co-op Brand 8	−0.108***	−0.04	−0.061
	(−0.039)	(−0.034)	(−0.059)
Co-op Brand 9	−0.033	0.035	0.107***
	(−0.042)	(−0.041)	(−0.036)
IOF Brand 10	0.028	−0.123**	0.014
	(−0.059)	(−0.052)	(−0.067)
Co-op Brand 11	−0.118**	0.075**	0.085
	(−0.047)	(−0.031)	(−0.082)
Co-op Brand 12	−0.048	0.036	−0.028
	(−0.049)	(−0.047)	(−0.094)
IOF Brand 13	0.102	0.076**	0.123***
	(−0.091)	(−0.032)	(−0.038)
IOF Brand 14	0.191***	0.090**	0.075*
	(−0.040)	(−0.038)	(−0.040)

(*Continued*)

Table 2. (*Continued.*)

	Price < €12.5	€12.5 < Price ≤ €26	€26 < Price ≤ €100
DV: Vivino rating	Model 1	Model 2	Model 3
Co-op Brand 15	−0.037	−0.069*	−0.171***
	(−0.066)	(−0.041)	(−0.053)
IOF Brand 16	0.058	−0.054	0.006
	(−0.095)	(−0.040)	(−0.042)
IOF Brand 17	−0.095	0.015	0.104*
	−0.096	−0.025	−0.054
Co-op Brand 18	−0.06	−0.046*	
	(−0.049)	(−0.024)	
Co-op Brand 19	0.003	0.017	0.055
	(−0.046)	(−0.061)	(−0.193)
IOF Brand 20		−0.08	−0.136
		(−0.067)	(−0.096)
Constant	*3.556****	*3.795****	*4.124****
	(−0.062)	*(−0.048)*	*(−0.079)*
N	450	855	418
r2	0.314	0.252	0.287
AIC	−247.527	−510.794	−130.491
BIC	−79.048	−315.999	30.928
Ll	164.763	296.397	105.245

Note: Estimated coefficient and (standard error). Ll = Loglikelihood. VIF values (min–max): Model 1 = 1.05–3.48; Model 2 = 1.02–2.07; Model 3 = 1.06–3.72. AIC = Akaike's information criterion; BIC = Bajesian information criterion.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

among coefficients of the same regressor in different price quantiles. Overall, several estimates appear to be heterogeneous among price quantiles (Table 4). The HQR model reveals that the GI effect is generally positive for all quantiles. PDO wines obtain significantly greater prices compared to PGI wines only in the first two quantiles (q25 and q50). As expected, younger vintages obtain lower average prices compared to 2015 or older vintages at all price points (between-vintages effect), with a negative peak in the upper price quantiles (q75 and q90). The price discount of younger bottles against older vintages reaches −62.7% for high-priced wines but shrinks up a half in the first price quantile (Table 4). Moreover, the "old vintage" effect is most evident up to 2018 bottles, i.e., 4-year-old wines, while the price premium obtained from 2017 and earlier is mostly comparable. The test for equality of coefficients is significant for all vintage dummies, suggesting that the same vintage receives a significantly different price premium at different price quantiles.

In contrast, the performance of varietals in terms of price-per-bottle seems highly heterogeneous between different grape varieties but mostly homogeneous among different price segments. Bottles from the autochthonous Schiava, Müller Thurgau, and Pinot Blanc record a consistently lower price compared to other varieties across all quantiles. Pinot Blanc exhibits lower value discounts in the first and third price

Table 3. Hedonic quantile regression on price-per-bottle (DV)

	q25		q50		q75		q90	
	β	Std. Err.	β	Std. Err.	β	Std. Err.	β	Std. Err.
DOC	0.117	0.043***	0.118	0.045***	0.064	0.059	0.02	0.096
2015 or older vintage (reference)								
2016	−0.005	0.068	0.021	0.063	−0.081	0.067	−0.151	0.125
2017	0.021	0.044	−0.076	0.056	−0.161	0.062***	−0.3	0.094***
2018	−0.112	0.045***	−0.217	0.05***	−0.327	0.056***	−0.456	0.093***
2019	−0.257	0.041***	−0.46	0.046***	−0.592	0.057***	−0.773	0.087***
2020–2021	−0.366	0.038***	−0.64	0.044***	−0.826	0.054***	−0.986	0.082***
Other varietals (reference)								
Red/rosé blend	0.074	0.058	0.101	0.059*	0.151	0.089*	0.32	0.132**
White blend	0.002	0.082	0.144	0.086*	0.131	0.102	0.193	0.109*
Cabernets	0.119	0.074	0.056	0.091	0.461	0.193**	0.523	0.126***
Chardonnay	−0.087	0.045**	−0.083	0.069	0.004	0.084	0.012	0.095
Gewürztraminer	0.122	0.041***	0.115	0.043***	0.077	0.067	0.062	0.088
Lagrein	0.055	0.045	0.059	0.043	0.001	0.053	0.061	0.098
Merlot	−0.084	0.073	0.036	0.114	0.068	0.082	0.084	0.138
Müller Thurgau	−0.245	0.055***	−0.268	0.057***	−0.377	0.09***	−0.274	0.138**
Pinot Blanc	−0.135	0.051***	−0.059	0.056	−0.105	0.055**	−0.125	0.096
Pinot Gris	−0.092	0.049*	−0.078	0.046*	−0.074	0.058	0.012	0.092
Pinot Noir	0.171	0.047***	0.19	0.041***	0.09	0.059	0.112	0.099
Sauvignon Blanc	0.061	0.046	0.085	0.049*	0.056	0.062	0.066	0.101
Schiava	−0.202	0.057***	−0.209	0.048***	−0.295	0.065***	−0.205	0.096**
Teroldego	−0.096	0.064	−0.161	0.095*	−0.111	0.133	−0.107	0.119
Other producer brands (reference)								
IOF Brand 1	0.137	0.034***	0.056	0.044	−0.023	0.065	−0.058	0.09
Co-op Brand 2	0.163	0.049***	0.127	0.068*	0.178	0.079**	0.182	0.104*
Co-op Brand 3	−0.003	0.052	0.092	0.067	0.074	0.08	0.201	0.116*
Co-op Brand 4	−0.016	0.047	−0.013	0.051	−0.066	0.061	−0.146	0.089*
Co-op Brand 5	−0.049	0.055	−0.107	0.043**	−0.146	0.07**	−0.148	0.108
Co-op Brand 6	−0.054	0.041	−0.099	0.056*	−0.137	0.072*	0.054	0.18
IOF Brand 7	0.19	0.113*	0.148	0.073**	0.251	0.074***	0.11	0.085
Co-op Brand 8	−0.093	0.04**	−0.111	0.049**	−0.217	0.061***	−0.318	0.076***
Co-op Brand 9	−0.06	0.051	−0.064	0.073	0.131	0.105	0.148	0.123
IOF Brand 10	0.079	0.048	0.09	0.077	0.249	0.123**	0.2	0.12*
Co-op Brand 11	−0.066	0.075	−0.082	0.064	−0.062	0.099	−0.066	0.221

(*Continued*)

Table 3. (*Continued.*)

	q25		q50		q75		q90	
	β	Std. Err.	β	Std. Err.	β	Std. Err.	β	Std. Err.
Co-op Brand 12	−0.001	0.042	−0.124	0.064**	−0.17	0.071***	−0.225	0.107**
IOF Brand 13	0.286	0.098***	0.431	0.129***	0.446	0.102***	0.441	0.128***
IOF Brand 14	0.046	0.053	0.07	0.076	0.145	0.126	0.233	0.193
Co-op Brand 15	−0.015	0.039	−0.096	0.053*	−0.139	0.081*	−0.239	0.128*
IOF Brand 16	0.324	0.068***	0.332	0.101***	0.326	0.103***	0.307	0.136**
IOF Brand 17	0.17	0.064***	0.161	0.057***	0.023	0.047	−0.119	0.076
Co-op Brand 18	−0.612	0.078***	−0.64	0.094***	−0.729	0.08***	−0.814	0.085***
Co-op Brand 19	−0.214	0.069***	−0.2	0.084**	−0.26	0.079***	−0.351	0.187*
IOF Brand 20	0.792	0.1***	0.968	0.145***	0.779	0.148***	0.643	0.158***
constant	2.637	0.057***	3	0.059***	3.446	0.08***	3.854	0.12***

Note: $n = 1{,}723$. Pseudo R^2 q25 = 0.23; q50 = 0.27; q75 = 0.29; q90 = 0.31. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.
The DV is the logarithm of price-per-bottle. The 25% quantile (q25) corresponds to 12.5 €/bottle; the 50% (q50) to 16.9 €/bottle; the 75% (q75) to 26.5 €/bottle; and the 90% (q90) to 39.9 €/bottle. VIF values (min–max): 1.34–6.09.

quantiles (13% and 10%), respectively, as shown in Table 4. On the contrary, Pinot Noir, red/rosé blends, and Gewürztraminer bottles benefit from price premia in the market. Gewürztraminer and Pinot Noir get relatively high price premia at low and medium price points, i.e., q25 and q50 (referring to Table 4). Cabernets have a significant but heterogeneous pricing, with a 60%–70% premium among high-priced bottles (q75 and q90; Table 4). Red and blends show similar behavior in the upper part of the price distribution (q90).

Looking at producer effects, the price-performance among co-op brands differs but appears essentially negative. Only one co-op brand obtains about 20% higher prices in all the quantiles, but it is mostly significant at q25 and q75, while the bottles from many other cooperatives are consistently sold at lower prices.

IV. Discussion and conclusions

This paper provides a first analysis of consumer ratings and how they respond to community effects (i.e., how often a wine has been rated) while accounting for essential wine attributes. We examine recent data for TAA wines obtained from Vivino.com. As a main result of this paper, we show that a small but significant online community effect on perceived quality exists, related to a wine's popularity among users of the Vivino community.

The regressions on Vivino ratings (RQ1) reveal that the factors affecting them seem to change depending on prices. Specifically, wines with a greater number of reviews received higher average ratings in the price ranges up to €26/bottle, while the number of reviews is no longer relevant for higher-end wines. This aligns with findings from Thrane's hypothetical survey experiment (2019), showing that positive peer reviews can affect consumer purchase choices for low- and medium-priced red wines,

Table 4. Price effects (%) and heterogeneity among estimated quantiles coefficients

	Price effect (%)				Quantiles heterogeneity test[a]
	q25	q50	q75	q90	*p*-Value
PDO	12.4	12.6	6.6	2.0	0.038**
2015 or older vintage (reference)					
2016	−0.5	2.1	−7.8	−14.0	0.118
2017	2.1	−7.3	−14.9	−25.9	0.001***
2018	−10.6	−19.5	−27.9	−36.6	0.000***
2019	−22.7	−36.9	−44.7	−53.8	0.000***
2020−2021	−30.7	−47.3	−56.2	−62.7	0.000***
Other varietals (reference)					
Red/rosé blend	7.6	10.6	16.3	37.7	0.452
White blend	0.2	15.5	14.0	21.2	0.382
Cabernets	12.6	5.7	58.6	68.7	0.016**
Chardonnay	−8.3	−8.0	0.4	1.2	0.282
Gewürztraminer	13.0	12.2	8.0	6.4	0.906
Lagrein	5.7	6.0	0.1	6.3	0.790
Merlot	−8.0	3.7	7.1	8.8	0.501
Müller Thurgau	−21.7	−23.5	−31.4	−23.9	0.582
Pinot Blanc	−12.7	−5.7	−10.0	−11.8	0.359
Pinot Gris	−8.8	−7.5	−7.1	1.2	0.840
Pinot Noir	18.6	20.9	9.4	11.9	0.866
Sauvignon Blanc	6.3	8.8	5.7	6.8	0.687
Schiava	−18.3	−18.9	−25.5	−18.6	0.980
Teroldego	−9.2	−14.8	−10.5	−10.1	0.019**
Other producer brands (reference)					0.481
IOF Brand 1	14.7	5.8	−2.3	−5.7	
Co-op Brand 2	17.8	13.5	19.4	20.0	
Co-op Brand 3	−0.3	9.6	7.7	22.3	
Co-op Brand 4	−1.6	−1.3	−6.3	−13.6	
Co-op Brand 5	−4.8	−10.2	−13.6	−13.8	
Co-op Brand 6	−5.3	−9.4	−12.8	5.5	
IOF Brand 7	21.0	15.9	28.5	11.7	
Co-op Brand 8	−8.9	−10.5	−19.5	−27.2	
Co-op Brand 9	−5.8	−6.2	14.1	16.0	
IOF Brand 10	8.3	9.4	28.3	22.2	
Co-op Brand 11	−6.4	−7.9	−6.0	−6.3	
Co-op Brand 12	−0.1	−11.7	−15.6	−20.1	

(*Continued*)

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Table 4. (*Continued.*)

	Price effect (%)				Quantiles heterogeneity test[a]
	q25	q50	q75	q90	*p*-Value
IOF Brand 13	33.1	53.9	56.1	55.4	
IOF Brand 14	4.7	7.3	15.6	26.2	
Co-op Brand 15	−1.5	−9.2	−12.9	−21.3	
IOF Brand 16	38.2	39.4	38.5	36.0	
IOF Brand 17	18.5	17.5	2.4	−11.2	
Co-op Brand 18	−45.7	−47.3	−51.7	−55.7	
Co-op Brand 19	−19.3	−18.1	−22.9	−29.6	
IOF Brand 20	120.7	163.2	117.9	90.2	

Note: $n = 1{,}723$. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$. Dark gray cells are significant at $p < 0.05$; light gray cells are significant at $p < 0.10$. Price effects in % are calculated for the categorical regressors based on Halvorsen and Palmquist (1980) as $(e^{\beta} - 1) \times 100$, where β is the estimated regression coefficient for the regressor considered.
[a] *H0: [q25] = [q50] = [q75] = [q90]*

while peer opinions are not significant for premium wines, for which other reputational aspects seem to be more important. For instance, rarity may play a role in the most expensive bottles, which are usually older (Gonen et al., 2021). Further research focusing on higher-end bottles is needed to explore the dynamics of reputation and community effects in this peculiar market segment, for example, by including expert evaluations as an instrument for product quality.

The descriptive analysis of average Vivino ratings by *lognrat* quantile unveils another interesting trait of the community effect that can be defined as "e-community subjective norm," i.e., the social pressure coming from peer opinions (Ajzen, 1991). Indeed, Figure 2 shows that ratings tend to be increasingly consistent as the number of evaluations increases. Thus, Vivino users may perceive the average rating of a wine judged by many users as an "established opinion" for which they would need more expertise or a strong motivation to deviate from (as suggested by Cialdini and Goldstein, 2004). Analyzing point data on single reviewers, their ratings on the same wine, and their profile could help shed light on how pre-existing consumer opinions affect future ones. Moreover, it is reasonable to believe that the community's opinion may affect wine purchase decisions ex-ante, both positively and negatively (as in Thrane, 2019). Indeed, highly rated wines may have more ratings because more people buy them due to their high popularity. On the contrary, wines "unanimously" rated lower may attract fewer consumers, and their number of ratings should stop increasing, reaching a plateau. Monitoring the relationship between average wine ratings and the number of ratings over time would help reveal whether this hypothesis holds and estimate the extent of the community's impact on actual purchase behavior.

Furthermore, the common belief that co-op wines are perceived as lower quality does not seem to hold for the TAA cooperative brands analyzed, at least after consumers have tasted the product. Results also confirm that varietals and brands that are highly appreciated by Vivino users also receive a greater price premium from the market. Thus, price may be a good indicator of perceived consumer quality and preferences in this respect independently from how and when wine quality is evaluated. Diversely, vintage and GI effects differ between estimated implicit prices and consumers' ratings, suggesting that similar attributes may have a different relevance based on the evaluation context considered.

When ratings are analysed, our model shows that PDO wines are not rated higher than PGIs for all price segments, suggesting GI rules and their restrictiveness do not impact how Vivino users perceive regional wine quality after consumption. Still, we cannot exclude a positive GI-label effect on consumers' ratings associated with the presence or absence of a GI label. Indeed, both PDO and PGI can be considered premium wines (Caracciolo et al., 2015; Di Vita et al., 2019).

As for vintages, consumers seem to appreciate younger bottles more than old ones, especially at lower price points. Even in the €12.5–€26 segment, all vintages report significantly greater ratings than 2015 or older bottles. The preference for younger wines is reduced above €26, where still some positive effects emerge for 2017 and 2018 bottles. This may be due to the regional orientation toward white wine production, accounting from 60% to 70% of the wine produced in South Tyrol[5] and Trentino.[6] Thus, TAA whites are more popular on the market and may be more appreciated than regional reds, which are usually the ones being aged (Gonen, 2021).

Overall, grape varieties do not seem to play a key role in determining average ratings. A positive exception is Gewürztraminer, which receives significantly higher ratings in the middle price segment. Gewürztraminer is a key variety for Alto Adige having grown in importance and now represents the second most important variety in the region.[7] Schiava and Müller Thurgau exhibit negative effects in determining average Vivino ratings.

Finally, most of the significant producer effects belong to co-op bottles although with heterogeneous performance among brands and different price ranges. Thus, our findings reveal that the long-told story of co-ops wine being perceived as lower quality (Caracciolo and Furno, 2020) may no longer be true, or at least, not for all TAA co-op brands. The importance of wine cooperatives in TAA and the Italian wine industry calls for additional analysis exploring co-op wine reputation and performance compared to other managerial and ownership forms. Our results should be further validated considering a broader range of wines covering more price points and co-op brands nationwide.

When comparing the ratings (RQ1) and hedonic quantile (RQ2) regression results, several differences emerge. First, the PDO label delivers a significant price premium compared to the PGI up to the 50% price quantile, even if consumers do not seem to rate PDO bottles higher than PGI ones. However, the PDO price premium becomes insignificant for higher-priced wines above the 50% price quantile, which may be due to individual and producer-related reputation effects that a wine has accumulated over time (Schamel and Ros, 2021). Still, the premium observed for PDO labels in the first half of the price distribution indicates that they may be effective higher-quality signals compared to PGI ones in these segments, perhaps prior to tasting the product. Indeed,

[5]https://www.suedtiroler-weinstrasse.it. Accessed 09/2023.

[6]https://www.suedtiroler-weinstrasse.it. Accessed 09/2023.

[7]https://www.suedtirolwein.com/de/weinsorten/weinsorten/68-0.html

the economic value of such labels is either strongly cost- or knowledge-related (e.g., Costanigro et. al., 2019; Jover et al., 2004; Teuber, 2011).

Vintage-specific performances show a strong heterogeneity across price quantiles, supporting the assumption that different price ranges should be analyzed separately. As expected, younger bottles get increasingly less expensive compared to older vintages, and such penalization significantly rises with price. This result is not surprising as aging wines imply greater production costs. Still, it contrasts with consumers' greater perceived value for younger wines, especially for bottles up to €26. Such discrepancies can be due to their actual suitability to enhance wine characteristics through aging, which strongly depends on multiple factors (García-Alcaraz et al., 2020), including regional characteristics and grape varieties, noting that TAA wine production is mostly white wine.

Similarly, production cost-related effects may apply to the misalignment emerging between implicit prices of some varietals (e.g., Pinot Noir) and community ratings. Still, most varietal price effects are consistent with consumer preferences (see, e.g., Gewürztraminer, Schiava, and Müller Thurgau). A limitation of this study in this respect is the inclusion of only two production areas, i.e., Trentino and Alto Adige. Performing the same analysis on national data would allow a better evaluation of the performance of local vs international varieties. This is particularly relevant for international varieties, which are cultivated across Italy and may thus produce wines with different organoleptic characteristics based on soil and climate conditions. For example, the price heterogeneity of Cabernet-based wines and their remarkable premium among high-end bottles should be further explored. Moreover, extending the dataset would allow to include additional regressors representing, among others, single GIs. Similarly to varieties, implicit prices for winery brands tend to align with those on consumer ratings with a few exceptions. Nevertheless, our results should be interpreted cautiously as the sample contains only wines self-selected by Vivino users and not all wines produced by a given producer brand are present in the dataset.

To conclude, sample descriptives provide some evidence of TAA wines having a stronger quality reputation than average wines on Vivino as their mean rating is above Vivino's overall average (Vivino, 2020). We further confirm that average ratings increase as bottles get more expensive and that price is an important quality signal leading to the creation of distinct market segments within the product category, in line with previous findings (Gokcekus and Nottebaum 2011; Oczkowski and Pawsey 2019). Further analysis could unveil whether this effect can be explained by a price-related bias in quality evaluation (Costanigro et. al., 2019; Jover et al., 2004; Teuber, 2011) or by superior wine quality.

The results of this analysis represent an important starting point to better understand wine value perception based on two ways of capturing it hedonic prices and consumer ratings, which have been little explored but may contain useful insights to practitioners and academics.

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References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179–211.

Akerlof, G. A. (1970). The market for "Lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488.

Almenberg, J., and Dreber, A. (2011). When does the price affect the taste? Results from a wine experiment. *Journal of Wine Economics*, 6(1), 111–121.

Anderson, M., and Magruder, J. (2012). Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *The Economic Journal*, 122(563), 957–989.

Bazen, S., Cardebat J. M., and Dubois M. (2023). The role of customer and expert ratings in a hedonic analysis of French red wine prices: From gurus to geeks? *Applied Economics*.

Bilgihan, A., Seo, S., and Choi, J. (2018). Identifying restaurant satisfiers and dissatisfiers: Suggestions from online reviews. *Journal of Hospitality Marketing & Management*, 27(5), 601–625.

Caracciolo, F., D'Amico, M., Di Vita, G., Pomarici, E., Dal Bianco, A., and Cembalo, L. (2016). Private vs. collective wine reputation. *International Food and Agribusiness Management Review*, 19(1030-2016-83139), 191–210.

Caracciolo, F., Di Vita, G., Lanfranchi, M., and D'Amico, M. (2015). Determinants of Sicilian wine consumption: Evidence from a binary response model. *American Journal of Applied Sciences*, 12(11), 794–801.

Caracciolo, F., and Furno, M. (2020). Hedonic functions, heterogeneous consumers, and wine market segmentation. *Journal of Agricultural and Resource Economics*, 45(2), 299–316.

Castriota, S., Corsi, S., Frumento, P., and Ruggeri, G. (2022). Does quality pay off? "Superstar" wines and the uncertain price premium across quality grades. *Journal of Wine Economics*, 17(2), 141–158.

Chandra, R., and Moschini, G. (2022). Product differentiation and the relative importance of wine attributes: US retail prices. *Journal of Wine Economics*, 17(3), 177–208.

Charters, S., and Pettigrew, S. (2007). The dimensions of wine quality. *Food Quality and Preference*, 18(7), 997–1007.

Chen, C.–W. (2017). Five-star or thumbs-up? The influence of rating system types on users' perceptions of information quality, cognitive effort, enjoyment and continuance intention. *Internet Research*, 27(3), 478–494.

Cialdini, R. B., and Goldstein, N. J. (2004). Social influence: Compliance and conformity. *Annual Review of Psychology*, 55, 591–621.

Costanigro, M., McCluskey, J. J., and Mittelhammer, R. C. (2007). Segmenting the wine market based on price: Hedonic regression when different prices mean different products. *Journal of Agricultural Economics*, 58(3), 454–466.

Costanigro, M., Scozzafava, G., and Casini, L. (2019). Vertical differentiation via multi-tier geographical indications and the consumer perception of quality: The case of Chianti wines. *Food Policy*, 83, 246–259.

Di Vita, G., Caracciolo, F., Brun, F., and D'Amico, M. (2019). Picking out a wine: Consumer motivation behind different quality wines choice. *Wine Economics and Policy*, 8(1), 16–27.

Fedoseev, V., Fedoseeva, S., and Herrmann, R. (2022). Implicit prices of attributes of fine German Riesling: magnitude and heterogeneity. *British Food Journal*, 125(4), 1245–1262.

Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., and Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. *Journal of Retailing*, 90(2), 217–232.

Frick, B. (2017). Some cooperatives produce great wines, but the majority does not: Complementary institutional mechanisms to improve the performance of an indispensable organizational form. *Journal of Wine Economics*, 12(4), 386–394.

García-Alcaraz, J. L., Montalvo, F. J. F., Cámara, E. M., de la Parte, M. M. P., Jiménez-Macías, E., and Blanco-Fernández, J. (2020). Economic-environmental impact analysis of alternative systems for red wine ageing in re-used barrels. *Journal of Cleaner Production*, 244, 118783.

Garrido, S. (2022). *Buffer Stocks, Wine Quality, and Wine Cooperatives in Franco's Spain and Beyond* (No. 2022/11).

Gavilan, D., Avello, M., and Martinez-Navarro, G. (2018). The influence of online ratings and reviews on hotel booking consideration. *Tourism Management*, 66, 53–61.

Gokcekus, O., and Nottebaum, D. (2011). The Buyer's Dilemma – whose rating should a wine drinker pay attention to? AAWE, Working Paper, No. 91, Economics.

Gonen, L. D., Tavor, T., and Spiegel, U. (2021). The positive effect of aging in the case of wine. *Mathematics*, 9(9), 1012.

Goodman, S. (2009). An international comparison of retail consumer wine choice. *International Journal of Wine Business Research*, 21(1), 41–49.

Hair, J. F., Black, W. C., Babin, B. J. and Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage

Halvorsen, R., and Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American economic review*, 70(3), 474–475.

Hong, S., and Pittman, M. (2020). eWOM anatomy of online product reviews: interaction effects of review number, valence, and star ratings on perceived credibility. *International Journal of Advertising*, 39(7), 892–920.

Hong, H., Xu, D., Wang, G. A., and Fan, W. (2017). Understanding the determinants of online review helpfulness: A meta-analytic investigation. *Decision Support Systems*, 102, 1–11.

Hu, X., and Yang, Y. (2021). What makes online reviews helpful in tourism and hospitality? A bare-bones meta-analysis. *Journal of Hospitality Marketing & Management*, 30(2), 139–158.

Jaeger, S. R., Mielby, L. H., Heymann, H., Jia, Y., and Frøst, M. B. (2013). Analysing conjoint data with OLS and PLS regression: A case study with wine. *Journal of the Science of Food and Agriculture*, 93(15), 3682–3690.

Jover, A. J. V., Montes, F. J. L., and Fuentes, M. D. M. F. (2004). Measuring perceptions of quality in food products: The case of red wine. *Food Quality and Preference*, 15(5), 453–469.

Kopsacheilis, O., Analytis, P. P., Kaushik, K., Herzog, S., Bahrami, B., and Deroy, O. (2023). Crowdsourcing the assessment of wine quality—evidence from Vivino. Available at https://ssrn.com/abstract=4355578 or http://dx.doi.org/10.2139/ssrn.4355578 (accessed August 21, 2023).

Kotonya, N., De Cristofaro, P., and De Cristofaro, E. (2018). Of wines and reviews: Measuring and modeling the Vivino wine social network. In *2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pp. 387–392. IEEE.

Lee, J., Park, D.–H., and Han, I. (2011). The different effects of online consumer reviews on consumers' purchase intentions depending on trust in online shopping malls. *Internet Research*, 21(2), 187–206.

Ling, B.–H., and Lockshin, L. (2003). Components of wine prices for Australian Wine: How winery reputation, wine quality, region, vintage, and winery size contribute to the price of varietal wines. *Australasian Marketing Journal*, 11(3), 19–32.

Lockshin, L., and Corsi, A. M. (2012). Consumer behaviour for wine 2.0: A review since 2003 and future directions. *Wine Economics and Policy*, 1(1), 2–23.

Lockshin, L., Jarvis, W., d'Hauteville, F., and Perrouty, J.–P. (2006). Using simulations from discrete choice experiments to measure consumer sensitivity to brand, region, price, and awards in wine choice. *Food Quality and Preference*, 17(3–4), 166–178.

Mastroberardino, P., Calabrese, G., Cortese, F., and Petracca, M. (2020). Sustainability in the wine sector: An empirical analysis of the level of awareness and perception among the Italian consumers. *British Food Journal*, 122(8), 2497–2511.

Mazzoli, E., and Palumbo, L. (2022). In vivino veritas: An investigation on consumers' quality perception and wine choice determinants. Available at https://ssrn.com/abstract=4114012 (accessed August 21, 2023).

Mobley, E. (2022). We tasted the top-rated wines in a hugely popular app. Are they actually any good? San Francisco Chronicle. Available at https://www.sfchronicle.com/food/wine/article/vivino-app-top-wines-17408037.php (accessed August 9, 2023).

Mueller, S., and Szolnoki, G. (2010). The relative influence of packaging, labelling, branding and sensory attributes on liking and purchase intent: Consumers differ in their responsiveness. *Food Quality and Preference*, 21(7), 774–783.

Neuninger, R., Mather, D., and Duncan, T. (2016). The effectiveness of extrinsic cues on different consumer segments: The case of wine awards. *Universal Journal of Management*, 4(11), 628–638.

Oczkowski, E. (2022). Estimating supply functions for wine attributes: A two-stage hedonic approach. *Journal of Wine Economics*, 17(1), 1–26.
Oczkowski, E., and Doucouliagos, H. (2015). Wine prices and quality ratings: A meta-regression analysis. *American Journal of Agricultural Economics*, 97(1), 103–121.
Oczkowski, E., and Pawsey, N. (2019). Community and expert wine ratings and prices. *Economic Papers: A Journal of Applied Economics and Policy*, 38(1), 27–40.
Outreville, J. F., and Le Fur, E. (2020). Hedonic price functions and wine price determinants: A review of empirical research. *Journal of Agricultural & Food Industrial Organization*, 18(2), 20190028.
Penagos-Londoño, G. I., Ruiz-Moreno, F., Sellers-Rubio, R., Del Barrio-García, S., and Casado-Díaz, A. B. (2023). Consistency of expert product reviews: An application to wine guides. *Wine Economics and Policy*, 11(2), 51–60.
Pennerstorfer, D., and Weiss, C. R. (2013). Product quality in the agri-food chain: Do cooperatives offer high-quality wine? *European Review of Agricultural Economics*, 40(1), 143–162.
Priilaid, D., and Hall, D. (2016). Price-quality heuristic correlation with rates of product consumption. *British Food Journal*, 118(3), 541–559.
Raiffeisenverband (2022). Available at https://www.raiffeisenverband.it/it/cooperative/agricoltura/vino (accessed June 22, 2023).
Ribeiro, T., Corsi, A., Lockshin, L., Louviere, J., and Loose, S. M. (2020). Analysis of consumer preferences for information and expert opinion using a discrete choice experiment. *Portuguese Economic Journal*, 19(1), 67–80.
Sáenz-Navajas, M.–P., Campo, E., Sutan, A., Ballester, J., and Valentin, D. (2013). Perception of wine quality according to extrinsic cues: The case of Burgundy wine consumers. *Food Quality and Preference*, 27(1), 44–53.
Schamel, G. H. (2014). Wine quality, reputation, denominations: How cooperatives and private wineries compete? In *BIO Web of Conferences (Vol. 3, p. 03008)*. EDP Sciences.
Schamel, G. H. (2015). Can German wine cooperatives compete on quality? In *BIO Web of Conferences (Vol. 5, p. 03003)*. EDP Sciences.
Schamel, G., and Anderson, K. (2003). Wine quality and varietal, regional and winery reputations: Hedonic prices for Australia and New Zealand. *Economic Record*, 79(246), 357–369.
Schamel, G., and Ros, A. (2021). Indicators of individual wine reputation for Friuli Venezia Giulia. *Italian Economic Journal*, 7(2), 323–339.
Schäufele, I., Herrmann, R., and Szolnoki, G. (2016). Erzielen Weine mit höherer Qualität höhere Preise? *Eine hedonische Preisanalyse zur DLG-Bundesweinprämierung.*
Teuber, R. (2011). Consumers' and producers' expectations towards geographical indications: Empirical evidence for a German case study. *British Food Journal*, 113(7), 900–918.
Thrane, C. (2019). Expert reviews, peer recommendations and buying red wine: Experimental evidence. *Journal of Wine Research*, 30(2), 166–177.
Tian G., Lu L., and McIntosh C. (2021). What factors affect consumers' dining sentiments and their ratings: Evidence from restaurant online review data. *Food Quality and Preference*, 88, 104060.
Vivino (2020). The vivino wine rating system: Credibility of the crowd. Vivino. Available at https://www.vivino.com/wine-news/vivino-5-star-rating-system (accessed April 12, 2022).
Weinwirtschaft (2022). Ausgezeichnete genossenschaften. Meininger. Available at https://www.meininger.de/wein/verkostungen/ausgezeichnete-genossenschaften (accessed July 30, 2022).
Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Cengage Learning.
Yan, X., Wang, J., and Chau, M. (2015). Customer revisit intention to restaurants: Evidence from online reviews. *Information Systems Frontiers*, 17(3), 645–657.

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