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Crowd-sourcing the assessment of wine quality

Orestis Kopsacheilis,

with Pantelis P. Analytis, Karthikeya Kaushik, Stefan M. Herzog, Bahador Bahrami and Ophelia Deroy

Naxos, July, 2023

American Association
of Wine Economists

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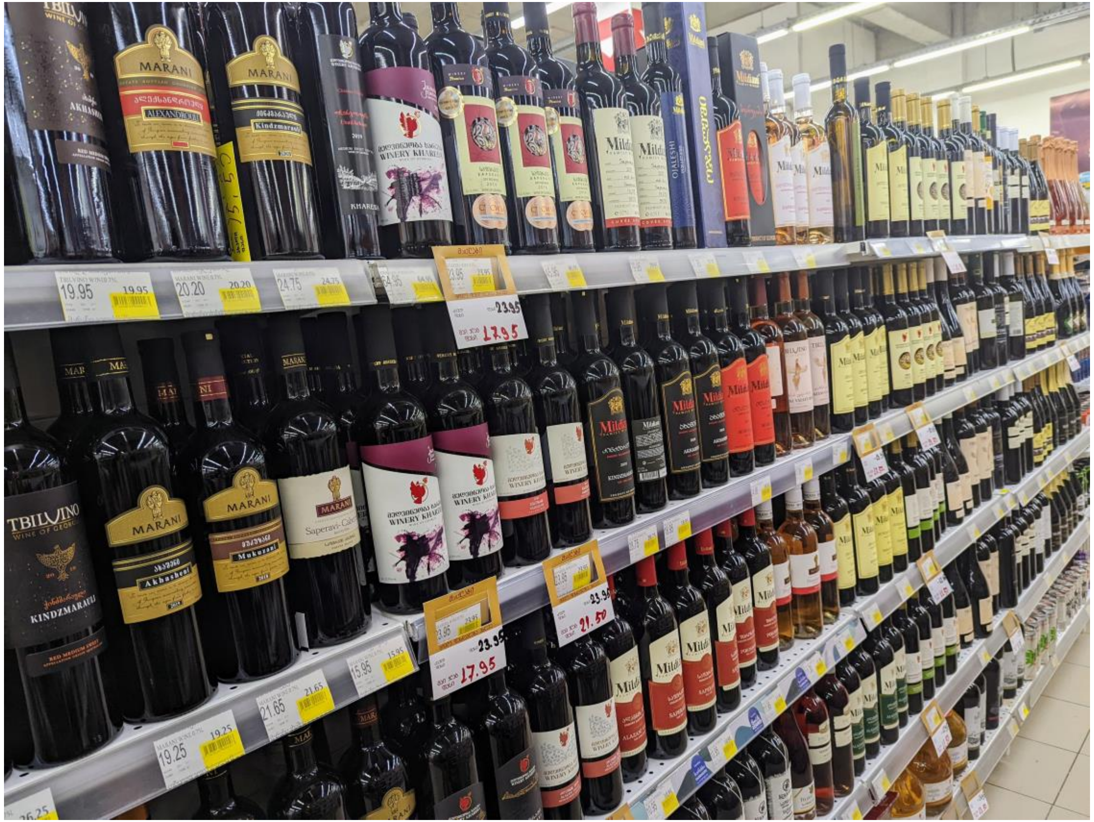

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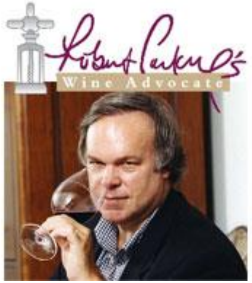
Markets

- Price

<u>Markets</u>

- Price

<u>Experts</u>

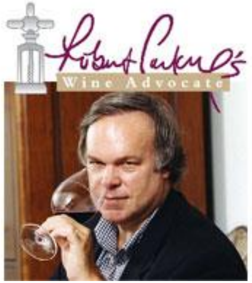


- Singular judgements

Markets

- Price

Experts



- Singular judgements

Crowds

- Aggregate scores from crowd-sourcing platforms

Markets and Experts

Price:

- Correlation between price and (perceived) quality is only moderate: 0.30 (meta-analysis by Oczkowski and Doucouliagos, 2015)
- It may lead to disappointments (i.e., experiencing relatively low quality when buying more expensive wines)
- It may restrict the opportunities to find good bargains (i.e., relatively high quality when buying less expensive wines).

Experts:

- Experts' reviews are not ubiquitous – most labels do not have such (reliable) ratings
- Experts' tastes may differ from amateurs' tastes (Goldstein et al., 2008)

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What about crowds?

Markets

- Price

Experts

- Singular judgements

Crowds

- Aggregate scores from crowd-sourcing platforms

"Wisdom of the crowds" ↔ "Conventional wisdom"

Amateur reviewers

Professional Critics






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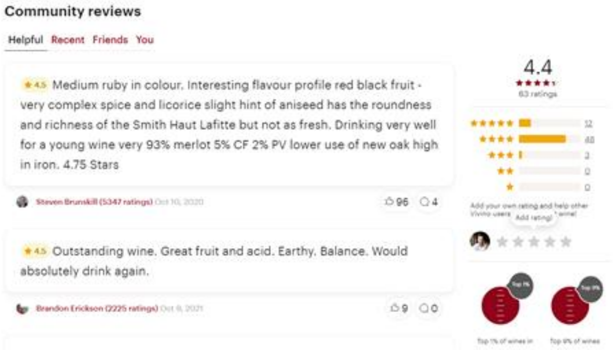
Our data set



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Our data set

- Red wines from Bordeaux
- Featured in En Primeur – match with prof. critics’ scores
- ~40,000 reviews
- 371 wines: 41 Chateaux – 13 vintages (2004 – 2016)

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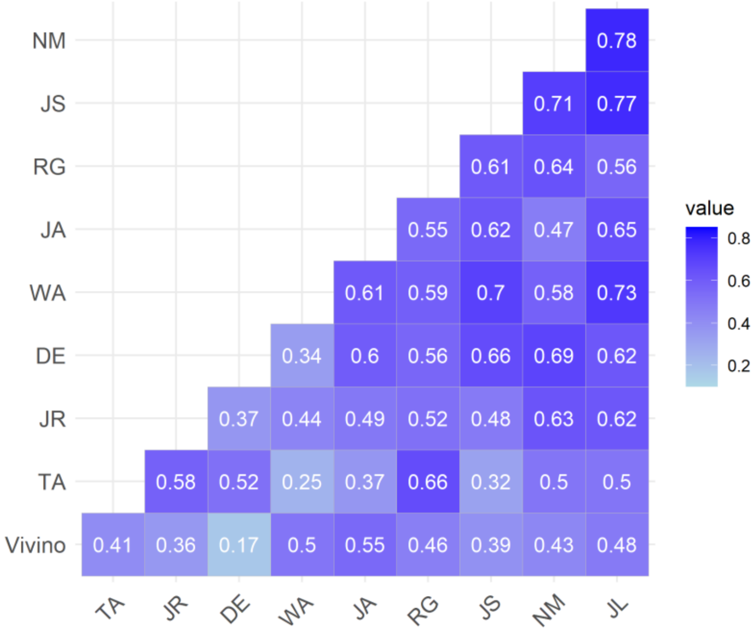
Correlations between experts’ scores and Vivino’s ratings



JR: Jancis Robinson; WA: the Wine Advocate;
Jancis Robinson (JR), the Wine Advocate (WA); TA: Tim Atkin;
JS: James Suckling; JL: Jeff Leve; De: Decanter; JA: Jane Anson,
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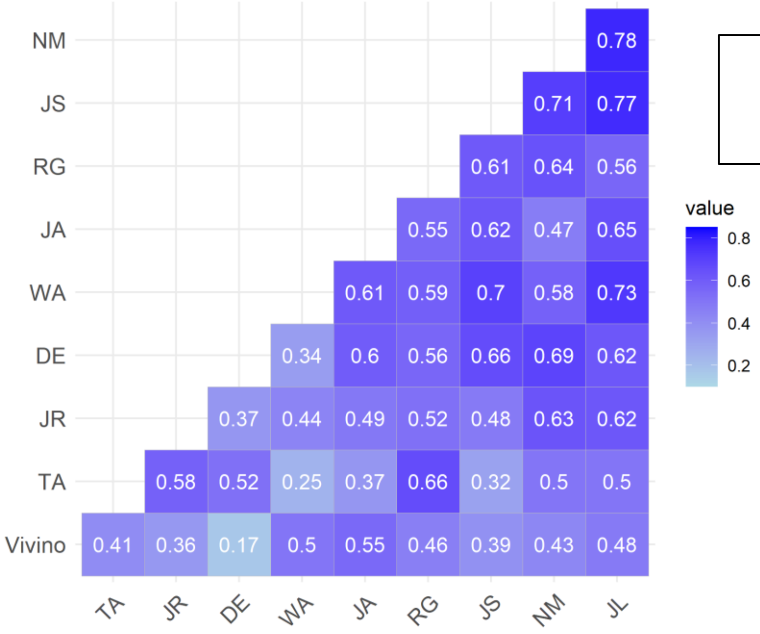

Result 1: Vivino amateurs correlate substantially with expert critics

BUT

the average correlation is lower than that between expert critics

JR: Jancis Robinson; WA: the Wine Advocate;
Jancis Robinson (JR), the Wine Advocate (WA); TA: Tim Atkin;
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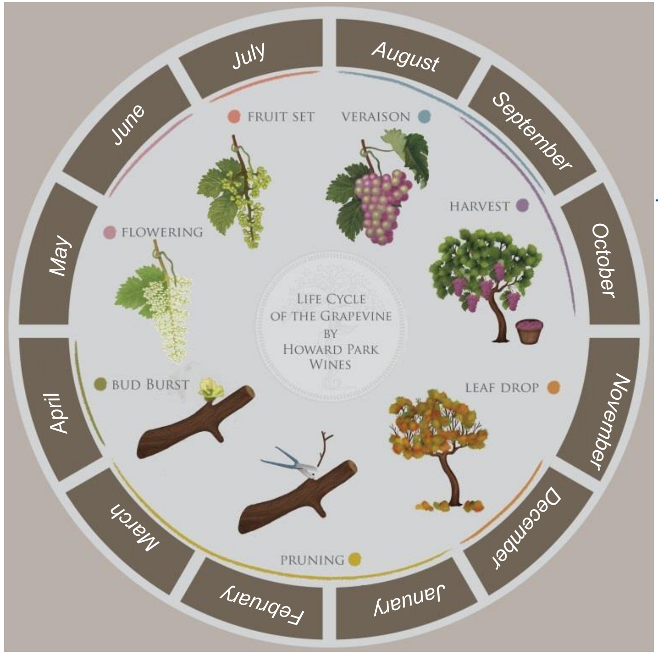
Wine and weather conditions

Growing season:
April - September



Pre-vintage season:
October - March

Wine and weather conditions – the Bordeaux equation

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PREDICTING THE QUALITY AND PRICES OF BORDEAUX WINE*

Orley Ashenfelter

Table 2 – Regressions of the (Logarithm of) Price of Different Vintages of a Portfolio of Bordeaux Chateau Wines on Weather Variables

Independent Variables	(1)	(2)	(3)
Age of vintage	0.0354 (0.0137)	0.0238 (0.00717)	0.0240 (0.00747)
Average temperature over growing season (April-September)		0.616 (0.0952)	0.608 (0.116)
Rain in August		-0.00386 (0.00081)	-0.00380 (0.000950)
Rain in the months preceding the vintage (October-March)		0.001173 (0.000482)	0.00115 (0.000505)
Average temperature in September			0.00765 (0.0565)

Notes: All regressions use as data the vintages of 1952-1980, excluding the 1954 and 1956 vintages, which are now rarely sold; all regressions contain an intercept, which is not reported.

Standard errors are in parentheses

Table 1: Determinants of wine ratings

	Dependent variable:	
	Vivino	Critics
	(1)	(2)
Constant	-8.078^{***}	-14.027^{***}
	(1.658)	(1.462)
AvgTempGrow	0.665^{***}	0.995^{***}
	(0.106)	(0.093)
RainAug	-0.007^{***}	-0.007^{***}
	(0.001)	(0.001)
RainPrecedGrow	0.0002	0.004^{***}
	(0.001)	(0.0005)
TempSept	-0.215^{***}	-0.319^{***}
	(0.039)	(0.035)
Observations	371	371
Log Likelihood	−418.459	−375.868
Akaike Inf. Crit.	850.918	765.736
Bayesian Inf. Crit.	878.331	793.150

Result 2.a.: Vivino ratings mirror the response of critics' towards weather conditions.

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Result 2.a.: Vivino ratings mirror the response of critics' towards weather conditions.

Result 2.b.: Professionals' and amateurs' ratings are sensitive to changes in objective markers of grape quality

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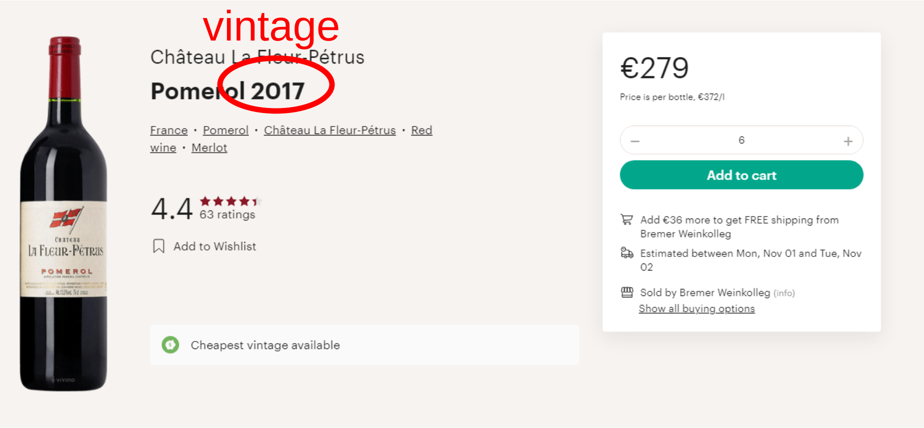
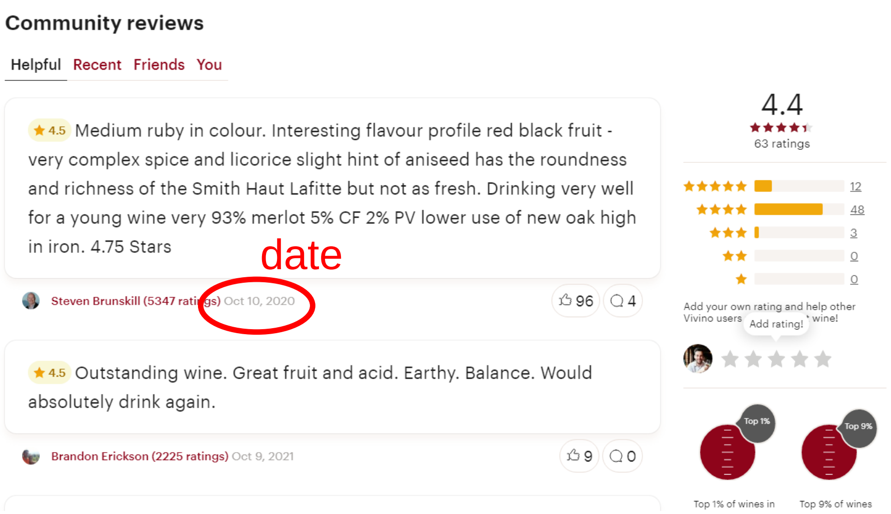
Our data set

$$Age\ of\ wine = Date\ of\ Review - Vintage$$





The aging factor

Table 5: Determinants of wine ratings for Vivino amateurs and professional critics

	Dependent variable:		
	Critics	Vivino	Vivino
	(1)	(2)	(3)
Constant	−14.027***	−8.078***	−3.156***
	(1.462)	(1.658)	(0.514)
AvgTempGrow	0.995***	0.665***	0.231***
	(0.093)	(0.106)	(0.033)
RainAug	−0.007***	−0.007***	−0.003***
	(0.001)	(0.001)	(0.0004)
RainPrecedGrow	0.004***	0.0002	0.0003
	(0.0005)	(0.001)	(0.0002)
TempSept	−0.319***	−0.215***	−0.082***
	(0.035)	(0.039)	(0.013)
Age			
Observations	371	371	2,450
Log Likelihood	−375.868	−418.459	−1,865.092
Akaike Inf. Crit.	765.736	850.918	3,746.184
Bayesian Inf. Crit.	793.150	878.331	3,792.615
Note:			*p<0.1; **p<0.05; ***p<0.01

The aging factor

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	(0.093)	(0.106)	(0.033)
RainAug	−0.007***	−0.007***	−0.003***
	(0.001)	(0.001)	(0.0004)
RainPrecedGrow	0.004***	0.0002	0.0003
	(0.0005)	(0.001)	(0.0002)
TempSept	−0.319***	−0.215***	−0.082***
	(0.035)	(0.039)	(0.013)
Age			0.044***
			(0.003)
Observations	371	371	2,450
Log Likelihood	−375.868	−418.459	−1,865.092
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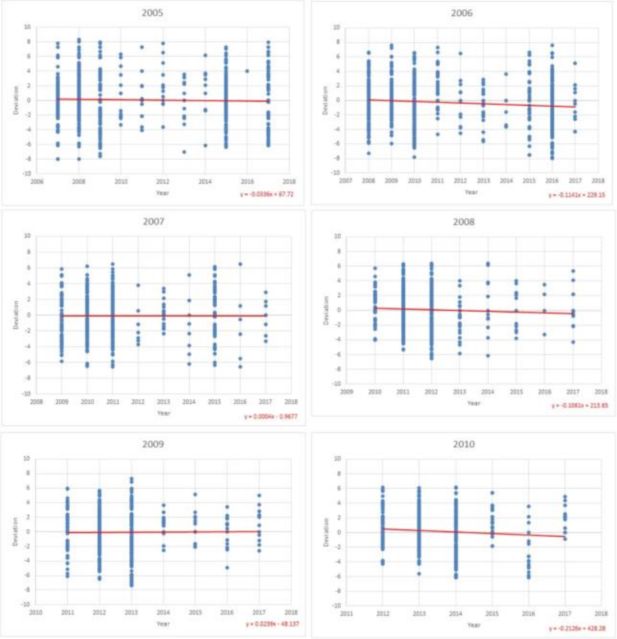
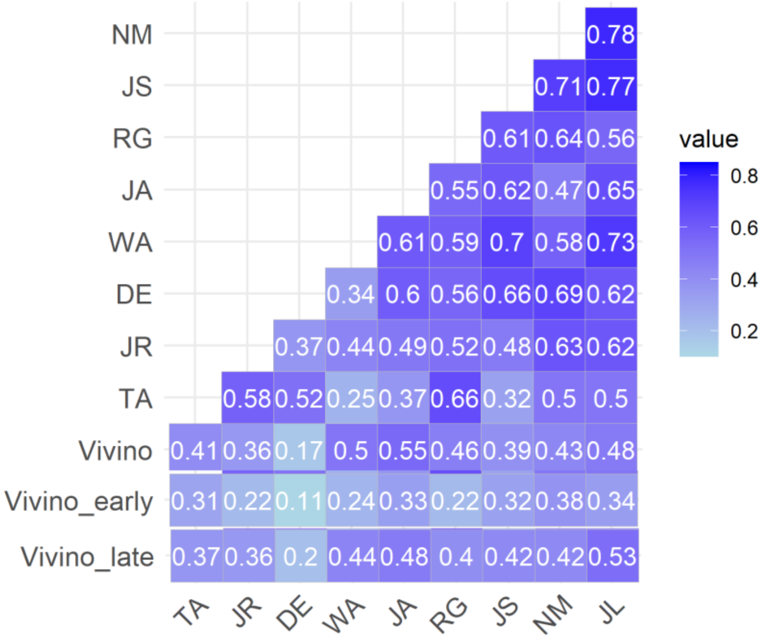
Note: *p<0.1; **p<0.05; ***p<0.01

Renotations by critics



	Reputation of the vintage	Average GWS	Leading coefficent	Trend
Vintage 2005	Excellent	91.8	-0.034	=
Vintage 2006	Common	90.21	-0.114	↓
Vintage 2007	Low	89.34	0.0004	=
Vintage 2008	Common	90.69	-0.106	↓
Vintage 2009	Excellent	92.51	0.024	=
Vintage 2010	Excellent	92.5	-0.213	↓

Amateurs vs Critics: a difference in scope



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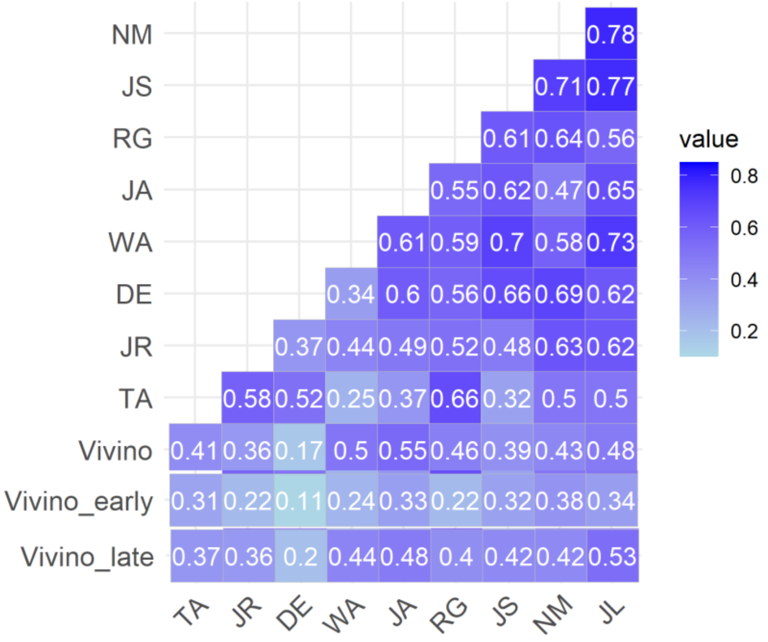

Result 3: Apparent differences in taste between amateurs and professionals are actually differences in scope: professionals are more forward looking

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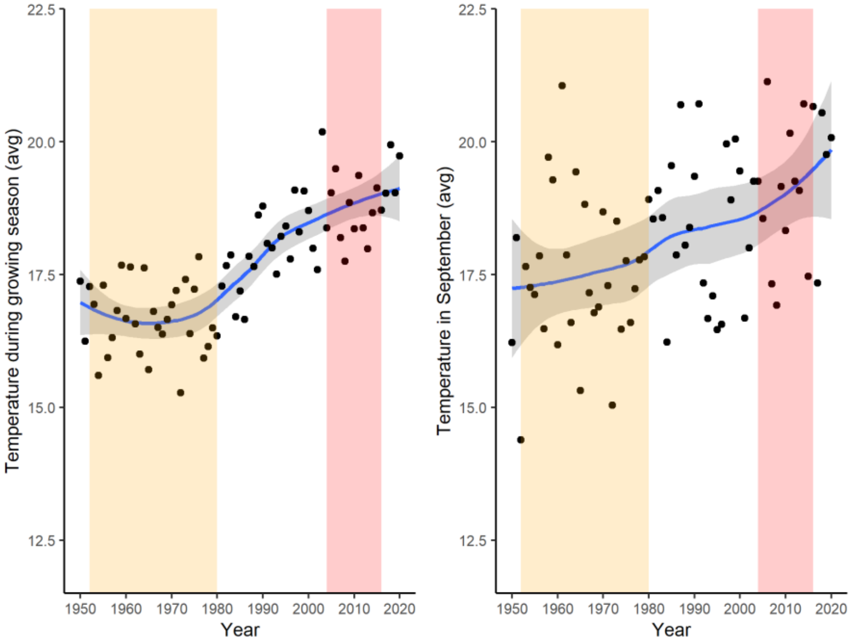
Rain in the months preceding the vintage (October-March)		0.001173 (0.000482)	0.00115 (0.000505)
Average temperature in September			0.00765 (0.0565)
R^2	0.212	0.828	0.828
Root mean squared error	0.575	0.287	0.293

Notes: All regressions use as data the vintages of 1952-1980, excluding the 1954 and 1956 vintages, which are now rarely sold; all regressions contain an intercept, which is not reported.

Standard errors are in parentheses

Global warming



- Higher temperatures in cooler climates are generally beneficial for grapes (Jones and Davis, 2000; Jones and Storchmann, 2001; Van Leeuwen et al., 2009).
- But they are not a panacea:
  - They can inhibit biochemical pathways or physiological processes essential for the production of quality grapes (Deloire et al., 2004).
  - In extreme cases, they can cause premature veraison, high grape mortality through abscission, enzyme inactivation and partial or total failure of flavor ripening (Mullins et al., 1992).

Global warming

Adapting **practices**

The strategies for adapting come into play for every vintage or at the time of each planting:

- Delay pruning date
- Increase vine trunk height to reduce leaf area
- Limit leaf thinning to protect grapes from sun
- Choose later-ripening varieties and rootstocks that ae more resistant to water stress
- Rethink plot sites
- Adapt harvesting date and harvest at night
- Reduce plant density

Source: “Bordeaux in the face of climate change - 2019 press release” – by Bordeaux Wine Council (CIVB)

Summary

- Take-home message 1: There is ‘wisdom’ in the wine-loving crowds.
  - Vivino ratings correlate substantially with expert scores and mirror optimal weather conditions

- Take-home message 2: Systematic differences of ratings with experts can be accounted by difference in scope: Vivino ratings focus on immediate pleasure
  - Implication: *is the wine intended for future investment or to impress peers at tonight’s dinner party?*

- Take-home message 3: Although higher temperatures during growing season are generally good, ratings are negatively affected when higher temperatures persist during veraison.
  - Bad news: to the extent that this is a consequence of global warming, it is about to get worse…
  - Good news: some wine regions have started adapting their bio-economy accordingly

Questions?

Additional resources

www.kopsacheilis.com

Contact

orestis.kopsacheilis@tum.de

Appendix

Wine = Chateaux + vintage

Chateaux

Château Latour-Martillac

Pessac-Léognan (Grand Cru Classé de Graves)

2014

France · Pessac-Léognan · Château Latour-Martillac · Red wine · Blend

3.9 ★★★★ 864 ratings

Add to Wishlist

Château Latour-Martillac

Pessac-Léognan (Grand Cru Classé de Graves)

2016

France · Pessac-Léognan · Château Latour-Martillac · Red wine · Blend

4.2 ★★★★ 698 ratings

Add to Wishlist

vintage

Wine and weather conditions

- Ashenfelter’s ‘Bordeaux equation’:
  - $\log(price) = \beta_0 + \beta_1 age + \beta_2\,(\mathrm{AvgTempGrow}) + \beta_3 RainAug + \beta_4 RainPrecedGrow + \beta_5 TempSept + \epsilon$
    - $\beta_1, \beta_2, \beta_4$: positive; β_3: negative; β_5: positive but not significant

Wine and weather conditions

- Ashenfelter's 'Bordeaux equation':
  - $\log(price) = \beta_0 + \beta_1 age + \beta_2\,(\mathrm{AvgTempGrow}) + \beta_3 RainAug + \beta_4 RainPrecedGrow + \beta_5 TempSept + \epsilon$
    - $\beta_1, \beta_2, \beta_4$: positive; β_3: negative; β_5: positive but not significant

- Our Vivino-equation:
  - $\log(rating) = \beta_0 + \beta_1 age + \beta_2\,(\mathrm{AvgTempGrow}) + \beta_3 RainAug + \beta_4 RainPrecedGrow + \beta_5 TempSept + \beta_6 \log(price) + \epsilon$

Wine and weather conditions

- Ashenfelter's 'Bordeaux equation':
  - $\log(price) = \beta_0 + \beta_1 age + \beta_2\,(\mathrm{AvgTempGrow}) + \beta_3 RainAug + \beta_4 RainPrecedGrow + \beta_5 TempSept + \epsilon$
    - $\beta_1, \beta_2, \beta_4$: positive; β_3: negative; β_5: positive but not significant

- Our Vivino-equation:
  - $\log(rating) = \beta_0 + \beta_1 age + \beta_2\,(\mathrm{AvgTempGrow}) + \beta_3 RainAug + \beta_4 RainPrecedGrow + \beta_5 TempSept + \beta_6 \log(price) + \epsilon$

- Differences with Ashenfelter's analysis:
  - Averaged ratings instead of auctioned prices
  - Observation period: 2004-2016 instead of 1952-1980
  - Level of analysis (and aggregation): wine instead of vintage

Table 2: Determinants of averaged Vivino ratings

	Dependent variable: Averaged Rating	
	(1)	(2)
log(price)		0.216^{***}
		(0.010)
Age	0.035^{***}	0.032^{***}
	(0.002)	(0.002)
AvgTempGrow	0.188^{***}	0.184^{***}
	(0.032)	(0.025)
RainAug	-0.001^{*}	-0.001^{**}
	(0.0003)	(0.0003)
RainPrecedGrow	0.001^{***}	0.001^{***}
	(0.0002)	(0.0001)
TempSept	-0.049^{***}	-0.049^{***}
	(0.012)	(0.009)
Constant	0.849	0.138
	(0.498)	(0.397)
Observations	5438	5424
Log Likelihood	−2450.181	−2260.451
Akaike Inf. Crit.	4916.363	4538.902
Bayesian Inf. Crit.	4969.172	4598.289
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$	

Notes: The (arithmetically) averaged Vivino-rating of a wine is regressed on climate variables, (the natural logarithm of) price and the age of each wine at the time when it was reviewed. The level of aggregation is at the age (measured in years) in which the wine was reviewed. The regression includes random effects at the level of the wine. We used R's lmer package from the lme4 library (Bates et al., 2014) to estimate this regression. The dataset we use for this regression comprises of a total of 5,438 observations(14 of which do not have information about price and, therefore, drop out in the second model). This includes a total of 832 wines (64 Chateaux observed in 13 vintages) that we observe for a period of 6.5 years (on average). Each Vivino rating ranges between 1 and 5 stars. Age is measured in years of distance between the vintage of a wine and the date that it was reviewed. 'AvgTempGrow': average temperature during the growing season (April - September) - measured in °C; 'RainAug': precipitation during August- measured in mm of water accumulated over the entire period; 'RainPrecedGrow': precipitation during the months preceding growth (October - March) -measured in mm of water accumulated over the entire period;'TempSept': average temperature during September - measured in °C. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

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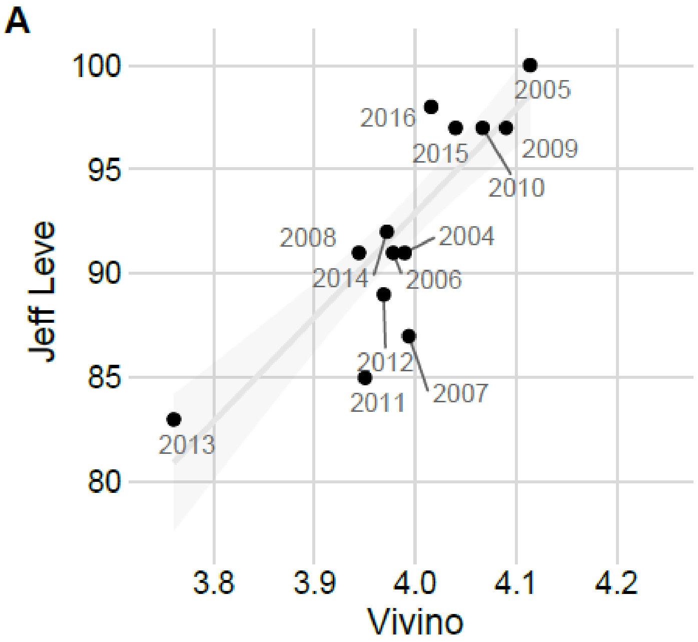
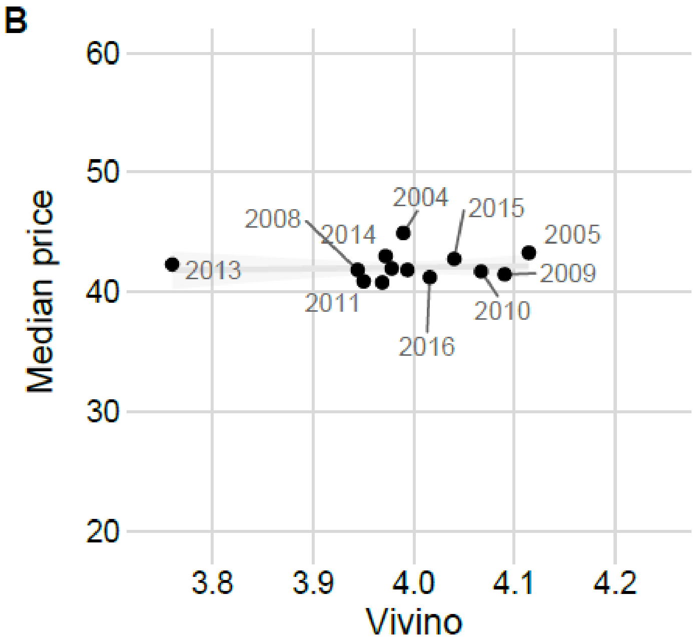
Vintage-level summary





Main method of analysis – linear regression model

- Multiple Ordinary Least Squares (OLS) regression:

$$rating = constant + \beta X + \epsilon$$

- X, is the matrix of independent variables that we use to predict the wines' ratings

- β, is the vector of coefficients representing the change in the mean response, E(*rating*), per unit increase in the associated predictor variable when all the other predictors are held constant.

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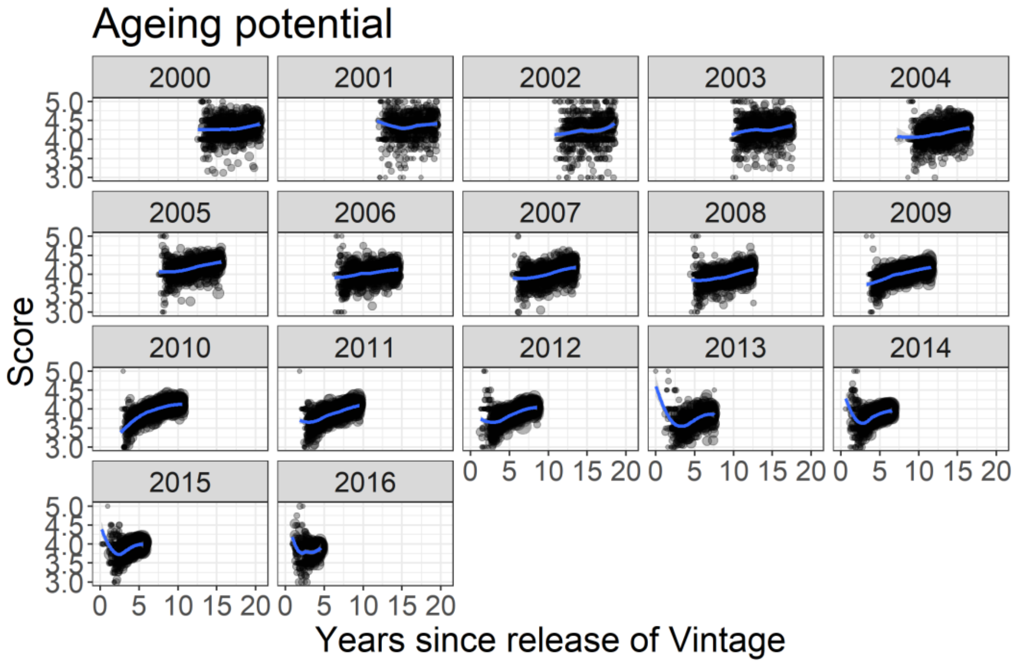
Moving forward (I)

- Can we dis-aggregate predictions about ageing potential?
  - We need to fit a hedonic-model that produces an inverse U-shaped pattern
  - We need more information on wines (grape composition, %alc., etc.)
  - We (prob.) need broader observation window



Moving forward (II): Beyond innate quality

- So far we focused on determinants of wine quality that are directly related to aspects of innate quality (age, weather conditions during production). What about behavioural factors?

- Herding effects and ratings bubbles:
  - Muchnik et al. (2013): positive social influence increases the likelihood of positive ratings – negative social influence is neutralized by crowd correction

- The few-get-richer:
  - Germano et al., (2019): attention attracted by a given class of news sources decreases with the number of news sources in that class. For example, if there are 20 news sources, the total number of clicks on left-leaning sources is larger when there are just 3 of these sources than when there are 17 of them

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Moving forward (II): Beyond innate quality

Moving forward (II): Beyond innate quality

Score before: social influence

#likes: popularity

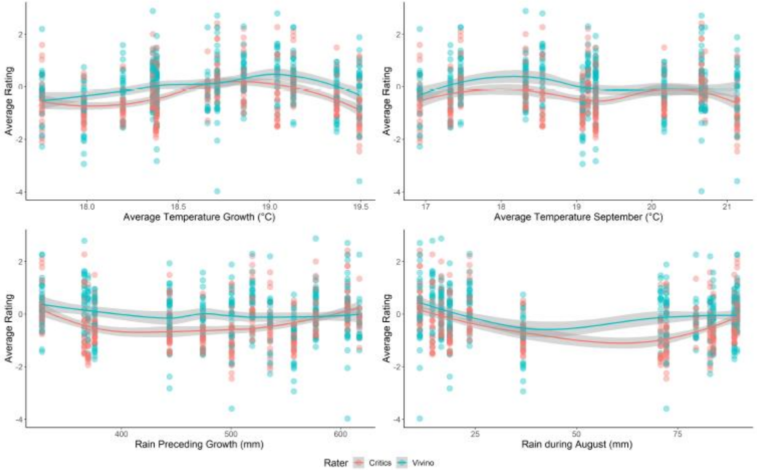

Figure 4: Ratings as a function of weather

Note. Curves and confidence bands show robust LOESS curves (locally estimated scatterplot smoothing using re-descending M-estimator with Tukey's biweight function) and their 95% confidence band.

Moving forward (II): Beyond innate quality

Table 6: Determinants of wine ratings

	Dependent variable:
	rating
Constant	1.022*** (0.060)
AvgTempGrow	0.029*** (0.004)
RainAug	−0.0004*** (0.00005)
RainPrecedGrow	−0.00000 (0.00002)
TempSept	−0.011*** (0.002)
age	0.006*** (0.0005)
log(price)	0.086*** (0.002)
log(likes)	−0.013*** (0.001)
log(ReviewLength)	−0.033*** (0.001)
ScoreBefore	0.588*** (0.006)
log(Volume of reviews)	0.025*** (0.001)
Observations	222,328
R^2	0.147
Note:	*p<0.1; **p<0.05; ***p<0.01

Few-get-rich: popularity of reviews

Table 6: Determinants of wine ratings

	Dependent variable:
	rating
Constant	1.022*** (0.060)
AvgTempGrow	0.029*** (0.004)
RainAug	−0.0004*** (0.00005)
RainPrecedGrow	−0.00000 (0.00002)
TempSept	−0.011*** (0.002)
age	0.006*** (0.0005)
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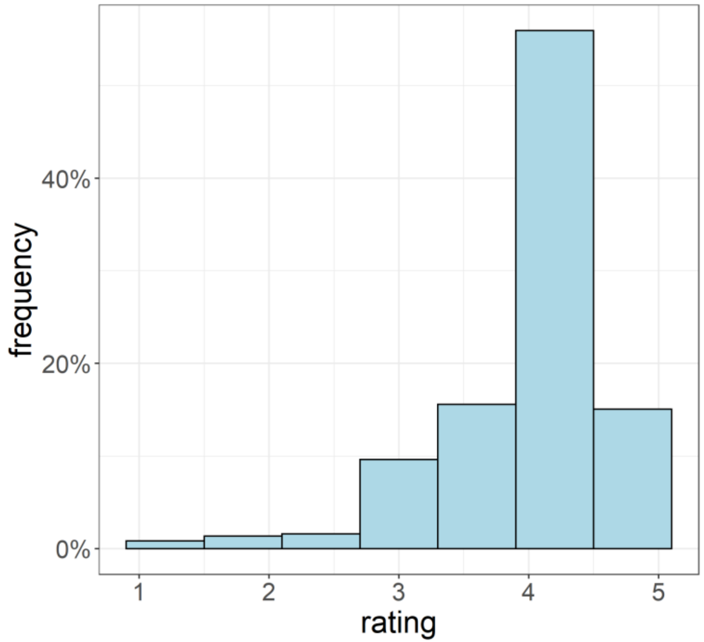
‘Bad’ reviews are more popular

Few-get-rich: popularity of reviews



Herding effects and ratings bubbles

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Positive social influence

Herding effects and ratings bubbles: an experiment

- Control: blind tasting – no information
- Treatment 1: low average score
- Treatment 2: high average score
- Hypothesis: The high average treatment score induces higher ratings

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Conclusions

- **Properties of wine:**
  - Result 1: price (when known) has a strong, positive correlation with subjective scores
  - Result 2: Amateurs' scores are significantly different than experts' – partly because they reflect more immediate hedonic aspects rather than forward looking prospects.
  - Result 3: people rate higher more aged wines (even when controlling for price)
  - Result 4:
    - Result 4.a. good weather conditions (for growing wine) are influence predictably reviewers' scores
    - Result 4.b. climate change (global warming) seems to mitigate part of the positive effect of insolation
- **Properties of reviews:**
  - Result 5: Positive herding: higher average scores induce more positive future ratings
  - Result 6: Bad reviews are more popular

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Logging to normalise