Journal of Wine Research

ISSN: 0957-1264 (Print) 1469-9672 (Online) Journal homepage: www.tandfonline.com/journals/cjwr20

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To cite this article: Ventura Charlin, Arturo Cifuentes, Luis Gonzales & Felipe Larrain (2023) Weather and wine quality in Chile's Casablanca Valley, Journal of Wine Research, 34:2, 122-139, DOI: 10.1080/09571264.2023.2205118

To link to this article: https://doi.org/10.1080/09571264.2023.2205118

JOURNAL OF WINE RESEARCH
2023, VOL. 34, NO. 2, 122–139
https://doi.org/10.1080/09571264.2023.2205118

Weather and wine quality in Chile's Casablanca Valley

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ABSTRACT

The Casablanca Valley, which is located in Chile's central region and is one of the eleven Wine Capitals of the World, presents a most unusual climate among the global wine regions: cold summers (Csc according to the Koppen classification). In this study we explore the relationship between weather and wine quality in Casablanca and we conclude that this relationship is quite different from what has been reported in reference to other wine regions. Specifically, we find that: (a) the weather affects the quality of red wines much more than that of white wines; (b) both, winter season and growing season weather variables play an important role in determining wine quality; (c) humidity and solar radiation also matter; and (d) absolute maximum and minimum temperatures during the grapevine cycle are also important explanatory variables. This is in stark contrast with several previous studies where the average temperature during the growing season and rainfall before the harvest season were found to be the most relevant weather variables to account for wine quality.

ARTICLE HISTORY
Received 17 August 2022
Accepted 2 April 2023

KEYWORDS
Casablanca Valley wines; wine ratings; weather-wine quality relationship; weather effects; Chilean wines; South American wines

JEL CLASSIFICATION CODES
C40; Q51; Q54

Introduction

The history of Chile's wine industry is straightforward and well-known. The country's wine production started shortly after the arrival of the Spanish conquistadors in the sixteenth century. In the middle of the nineteenth century there was a switch from Spanish to French grape varieties (this was roughly twenty years before the phylloxera epidemic decimated most European vineyards). By the end of the nineteenth century the industry was thriving as the latest French technology had been incorporated to the country's wine production and there are records of Chilean winemakers showcasing their products in French and British industry fairs. Nonetheless, during an important part of the twentieth century the industry faced some challenges due to restrictive legislations that, among other things, limited production and prohibited planting new vines. During the last fifty years, however, a sequence of market-friendly reforms combined with the arrival of both, capital and technological know-how, mainly from France and California, has invigorated the Chilean wine industry. Today Chile produces 6% of the wine in the world and is known for its high-quality cabernet sauvignon. The wine regions are located in the

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central part of the country and benefit from a Mediterranean climate (Csb based on the Koppen classification). In 2021, Chile exported almost one-million liters of wine for a total value of US$ 2 billion. China, Brazil and the U.K. accounted for 40% of Chilean wine exports. In all, Chile has roughly 135,000 hectares dedicated to wine production (Flaño, 2022). This is the standard story behind the Chilean wine industry.[1]

The Casablanca Valley, which is located roughly half-way between the Andes mountains and the Pacific Ocean at a 33°19′ S latitude and at an average elevation of 300 meters, represents a singularity within the Chilean wine sector – its story differs in three important ways from the version described in the preceding paragraph. In essence, there is Casablanca, and there is the rest of the Chilean wine industry:

(1) The Casablanca winemaking industry is about fifty years old, young by any standard. Before 1980 this region was a rural area dedicated mostly to grazing. Around that time, Pablo Morande, a Chilean winemaker who was looking for a place to produce white wine, perceived certain similarities between this area and Carneros in California. His intuition proved to be correct. Today, the valley counts more than fifty wineries and boasts of more than 6,000 hectares of fine vines of which about one-third represents foreign investments (Kunc & Bas, 2009). It is the only location in Chile that belongs to the eleven Great Wine Capitals of the World, a global network of winemaking regions aimed at improving cooperation among them (Brethauer, 2020; Overton et al., 2012). Mendoza, across the Andes in Argentina, is the only other South American location that belongs to this prestigious association that also includes Bordeaux, Napa, Rioja, Florence and Cape Town.
(2) The valley's climate, temperate with cold summers (Csc based on the Koppen classification, where the 'c' stands for cold summer), is a rarity (Climate-Data.org, 2022; Saavedra et al., 2011). In fact, the rest of Chile's wine regions, like most of the Californian, French, and Australian winemaking regions, are characterized by warm summers, either Cfb or Csb climates, according to the Koppen characterization.
(3) Although Chile is mainly known for its red wines (in fact, the cabernet sauvignon is the industry flagship) the Casablanca Valley has focused on white wines (sauvignon blanc and chardonnay). Its red production, which is approximately one-third of the total output, is concentrated on pinot noir, not cabernet sauvignon.

In short, the uniqueness of Casablanca's climate – not only in the context of the Chilean winemaking regions, but also in relation to the global wine industry – coupled with the increasing export-oriented focus of this valley, makes investigating the relationship between weather and wine quality in Casablanca a subject worthy of attention.

Review of previous literature

Orley Ashenfelter was one of the first researchers who investigated the relationship between weather and wine quality. He relied on regression-based techniques which he applied to wines of the Bordeaux region and described the weather using average temperatures and cumulative rainfall at different stages of the grapevine life cycle (Ashenfelter, 2008; Ashenfelter & Jones, 2013; Byron & Ashenfelter, 1995). His main conclusion was that weather mattered; more specifically, he claimed that the temperature during the growing season and precipitation during the months preceding the vintage were the key drivers of wine quality. His pioneering effort led to extending this approach to wines of other regions such as Burgundy, Italy, Napa and Sonoma in California, and Australia (e.g. Corsi & Ashenfelter, 2019; Niklas & Rinke, 2020; Oczkowski, 2016a; Oczkowski, 2016b; Outreville, 2018; Ramirez, 2008).

Broadly speaking, Ashenfelter's findings were validated by subsequent research albeit with some nuances. For example, in the case of Bordeaux he reported models with a very high explanatory power (adjusted-R^2 of more than 80%). Other researchers, notwithstanding the relevance of the weather in terms of accounting for wine quality variations, have reported much lower adjusted-R^2. It is worth noting that the weather in the Bordeaux region varies a lot from year to year, in contrast to California or Australia, which enjoy more stable weather patterns. Hence, it is somewhat expected that the weather should offer less explanatory power in the stable-weather regions (Haeger & Storchmann, 2006; Henninger, 2018; McNeil, 2001). A recent article by Outreville and Le Fur provides a very detailed review of the empirical literature dealing with the use of statistical models to identify the determinants of wine prices and quality (Outreville & Le Fur, 2020). Also, an interesting meta-analysis is presented in the paper by Oczkowski and Doucouliagos (2015). Needless to say, the use of statistical models to assess or predict wine quality has not been entirely well received by wine-industry experts (Derbyshire, 2013; Passell, 1990).

Two trends emerge as salient upon reviewing this literature. First, most efforts have been oriented to explore the weather-wine quality relationship in the Northern Hemisphere. Wines from the Southern Hemisphere, with the exception of Australia, have received less attention (e.g. Oczkowski, 2016a; Oczkowski, 2016b). In the case of Chile, previous research has looked at the drivers behind prices (not quality), but without taking the weather into consideration. They have considered factors such as the type of grape, number of cases produced, the type of bottle employed or the neighborhood where the wine is sold (Gonzalez & Melo, 2008; Ortuzar-Gana & Alfranca-Burriel, 2010; Romo-Munoz et al., 2020; Troncoso & Aguirre, 2006). And more specifically, in the case of Casablanca, we are only aware of three articles dealing with the wine-related activity in the valley. One paper, which recognizes the uniqueness of the region's climate, focusses on using chemometric approaches combined with different statistical techniques to typify the different zones of the valley (Saavedra et al., 2011). A second paper gives a detailed account of how the valley reinvented itself in the last thirty years to become a serious wine producer (Overton et al., 2012). And a third study investigates whether wines produced in the Zona Alta and Zona Baja, the two historical zones in which the valley is divided, share the same anthocyanin profile (Cuneo et al., 2013). But a study investigating the weather-wine quality relationship in this area is still lacking.

Second, much has been learned in terms how the weather impacts wine quality. In fairness, however, most of it has been a confirmation of what wine producers already knew, for example, that excessive summer heat (say, temperatures higher than 30 °C) can be detrimental for grapes. Or that big temperature variations are undesirable (Gladstones, 1992; Goldammer, 2018; Jones, 2015; Urska, 2019). Nevertheless, we think more progress in this area is possible. For instance, weather models have been dominated by characterizations based on temperature and rainfall but neglecting other potentially relevant variables such as humidity and solar radiation. Also, given the relevance of big swings in temperature, a description based only on averages might be insufficient. In fact, to fully describe the effect of extreme temperatures we think that having access to daily data, rather than monthly averages, might be needed. Additionally, note that taking the average of daily differences between the maximum and minimum temperatures, as some authors have done, tends to smooth the extreme variations and might possibly mask the influence of such events. Finally, although all wine regions share some common climate elements, they also differ in some important aspects. For instance, California and the Bordeaux region in France, both enjoy a temperate climate, yet, in California, unlike Bordeaux, the summer is dry; Mendoza has an arid climate (Bwk) and unlike California, enjoys rain during the summer; and most of the Australian wine region is much more similar to that of France (both are Cfb) rather than California and the rest of Chile's central region (Csb). Remarkably, previous studies have not reported the precise Koppen climate classification of the regions under study which might give the unintended impression that the weather-wine quality relationship is less dependent on the local geography than it might seem. These observations should not be taken as a heavy-handed criticism of previous efforts; quite the contrary, they are possible because of the advances made by previous efforts. They should only be taken as an invitation to describe the weather features in a more refined manner and be open to the possibility that the weather-wine quality relationship is more locally driven than previously believed. Indeed, certain researchers have already made inroads in that direction. Henninger (2018), in his study of western U.S. wines, employed as additional independent variables the number of days in which the temperature exceeded 32°C, and, the number of days with temperatures below freezing. Niklas and Rinke (2020), on the other hand, incorporated the number of sunshine hours during winter.

Given this background, the aim of this study is not only to explore the weather-wine quality interaction in the Casablanca Valley region, but also to explore the merits of relying on a more detailed characterization of the potential weather effects.

Data and sources

Wine quality

Like a number of previous studies, we relied on Wine Spectator (WS) ratings as a proxy for wine quality (e.g. Haeger & Storchmann, 2006; Henninger, 2018; Ramirez, 2008). WS ratings offer two advantages: (i) they are determined by trained judges, in blind tests, who do not have any information regarding the suggested retail price; and (ii) the WS database is both global and extensive in terms of the number of years covered, thus, we think is more suitable than ratings provided by companies that are focused mostly on domestic markets. WS ratings are expressed as a score that goes from 50 (lowest) to 100 (top quality). Wines with a rating (score) equal or higher than 95 are considered a classic (great wines). Wines with ratings below 80 are considered mediocre or worse. The ratings information was downloaded from the company website (www.winespectator.com) and consisted of: rating, vintage (year), price, winery, and type of wine. Price refers to the U.S. suggested retail price for the standard 750 cc bottle, expressed in dollars of the vintage year.

Table 1. Wine data: descriptive statistics (ratings and prices), by wine type; 1993–2020 vintages.

Variables	N[b]	Avg.	Std. Dev.	Min.	Max.
Sauvignon Blanc Rating	291	85.99	2.27	77	90
Sauvignon Blanc Price[a]	291	19.21	6.86	11.00	55.00
Chardonnay Rating	345	85.87	3.27	63	91
Chardonnay Price[a]	345	21.01	9.06	8.00	64.00
Red wines Rating	317	86.51	3.34	75	93
Red wines Price[a]	317	27.11	13.90	11.00	91.00
Pinot Noir Rating	195	86.61	3.18	75	93
Pinot Noir Price[a]	195	27.50	14.55	11.00	85.00

[a]Price of 750 cc. bottle expressed in 2020 US$.
[b]*N* is the number of observations.

We are mindful that in economics prices have a long tradition of being used as a valid proxy for quality. In this case, however, we think that ratings are a better alternative. The reason is simple: the prices reported by the WS website are suggested retail prices based on the producer's opinion. That is, they are likely to be biased and certainly they are not the result of a dynamic supply-demand interaction under free market conditions. Wines with more tradition and a broader market appeal (e.g. Bordeaux) enjoy the benefit of an active secondary market and daily prices, provided, in this case, by Liv-ex (https://www.liv-ex.com). Other wines also enjoy the benefits of more active markets and there are indices that reflect their price fluctuations (e.g. Liv-ex provides price indices for certain Italian wines, and wines from the Burgundy and Rhone region). Chilean wines are not in that category. Thus, the WS ratings seem to be a good choice to represent quality. That said, prices were also downloaded due to their potential usefulness as control variables.

Table 1 summarizes the wine-related data. The white wine data consists of 636 observations: 291 correspond to sauvignon blanc (27 vintages; 1993, 1995-2020) and 345 represent chardonnay (27 vintages; 1993-2019). The chardonnay data includes 52 wineries while the sauvignon blanc data 50. The red wine data consists of 317 observations of which 195 refer to pinot noirs. It includes 45 wineries and covers 25 vintages, namely, 1995-2019. Figure 1 shows the ratings evolution by vintage. All in all, they exhibit an upward trend that suggests that the most important improvements occurred in the late 1990s-early 2000s. The big drop in reds' ratings observed in 2019 is probably not representative of a broader industry tendency as it is the result of only three observations, all from not very prestigious wineries.

Weather information

The weather data were obtained from three sources: (1) we used the Atlas de Riesgo Climático (https://arclim.mma.gob.cl) for the period 1979–2018, a platform maintained and operated by the Chilean Ministry of Environmental Affairs; (2) we complemented this information with additional data from the Red Agroclimática Nacional (https://www.agromet.cl), a platform managed by the Ministry of Agriculture; and (3) we further enhanced these data with observations we downloaded from the Center for Climate and Resilience Research's website (https://www.cr2.cl), which is part of a climate research effort carried out by a consortium of Chilean universities and funded by the Chilean Government Agency for Research and Development. The Casablanca

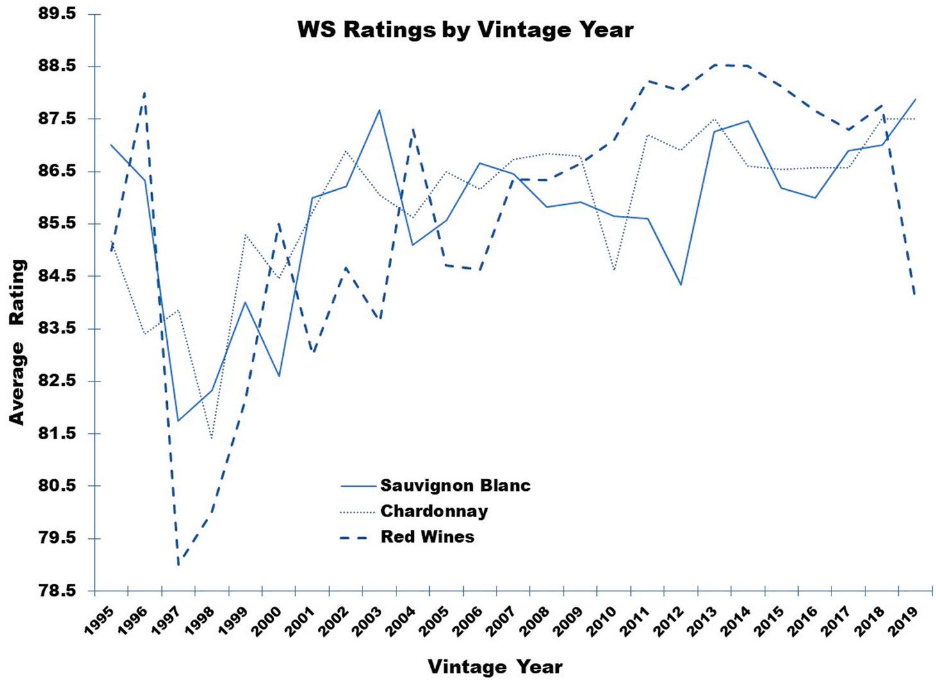

Figure 1. WS ratings by vintage year.

weather station is located at an altitude of 322 meters (latitude, 33°14′ S; longitude, 71° 27′ W).

Temperature and rainfall data correspond to daily observations. Temperature data consist of three data points: maximum temperature observed during the day (T_{max}); minimum temperature observed during the day (T_{min}); and the average temperature for the day, T, which is a representative figure based on measurements at three times during the day: 8 am, 2 pm, and 8 pm. Temperatures are expressed in degrees Celsius and rainfall, which is the cumulative value for the day, is expressed in millimeters. Note that Avg(T_{max}) is the average of all the daily maximum temperatures observed during the season. Max(T_{max}) is the highest (maximum) value considering all the daily maximum temperatures recorded during each season; Avg(T_{min}) is the average of all the daily minimum temperatures observed during the season and Min(T_{min}) is the lowest (minimum) value considering all the daily minimum temperatures recorded during each season.

Additionally, we obtained monthly information regarding humidity (average value expressed as percentage), and solar radiation (cumulative value for the month). Solar radiation, SR, is expressed in Kilowatt/m^2 (abbreviated as KW/m^2), that is, energy per unit of area. In theory, the peak value for solar radiation is 1 KW/m^2, that is, a location that enjoys 8 h of sunshine per day, in a typical month, will receive $30 \times 8 \times 1 = 240$ KW/m^2. Solar radiation is a proxy for sunshine days or hours and also for the level of cloudiness. Table 2 summarizes the weather data by season, based on the grapevine lifecycle. Figure 2 and Figure 3 show how the temperature and rainfall have evolved during recent years for each of the grapevine cycle seasons (winter, growing season, and harvest). The grapevine

Table 2. Weather variables: descriptive statistics (1993-2020).

Weather variables	Mean	Std. Dev.	C.V.[†] (σ/μ)	Min.	Max.
WINTER (Jun-Aug)					
Avg(T), °C	10.8	0.5	0.05	9.3	11.9
Avg(T_{max}), °C	15.7	0.6	0.04	14.0	16.7
Avg(T_{min}), °C	4.8	0.6	0.13	3.2	6.1
Max(T_{max}), °C	22.2	1.4	0.06	19.8	25.2
Min(T_{min}), °C	0.7	0.9	1.17	−0.8	2.3
Avg(Humidity), %	89.5	2.7	0.03	83.6	93.9
Cumulative Rain, mm	277.7	124.5	0.45	33.6	612.1
Cumulative SR, KW/m^2	175.6	50.7	0.29	68.0	276.0
GROWING SEASON (Sept-Feb)					
Avg(T), °C	15.8	0.4	0.02	15.1	16.8
Avg(T_{max}), °C	21.6	0.5	0.02	20.9	23.1
Avg(T_{min}), °C	9.1	0.3	0.03	8.5	9.7
Max(T_{max}), °C	28.1	1.0	0.04	26.4	30.3
Min(T_{min}), °C	2.8	0. 8	0.28	1.2	4.3
Avg(Humidity), %	78.7	2.7	0.03	69.2	81.6
Cumulative Rain, mm	61.3	53.9	0.88	0.0	220.1
Cumulative SR, KW/m^2	1295.5	108.7	0.08	1006.0	1428.0
HARVEST (Mar-Apr)					
Avg(T), °C	16.1	0.6	0.03	15.2	17.2
Avg(T_{max}), °C	22.2	0.6	0.03	21.4	23.4
Avg(T_{min}), °C	9.1	0.7	0.07	7.9	10.6
Max(T_{max}), °C	27.0	1.5	0.05	25.4	32.2
Min(T_{min}), °C	5.7	1.1	0.19	3.4	8.1
Avg(Humidity), %	79.2	2.3	0.03	74.9	84.6
Cumulative Rain, mm	33.2	45.6	1.37	0.0	209.9
Cumulative SR, KW/m^2	354.9	31.8	0.09	298.0	417.0

[a]C.V. stands for coefficient of variation, i.e. mean divided by standard deviation.

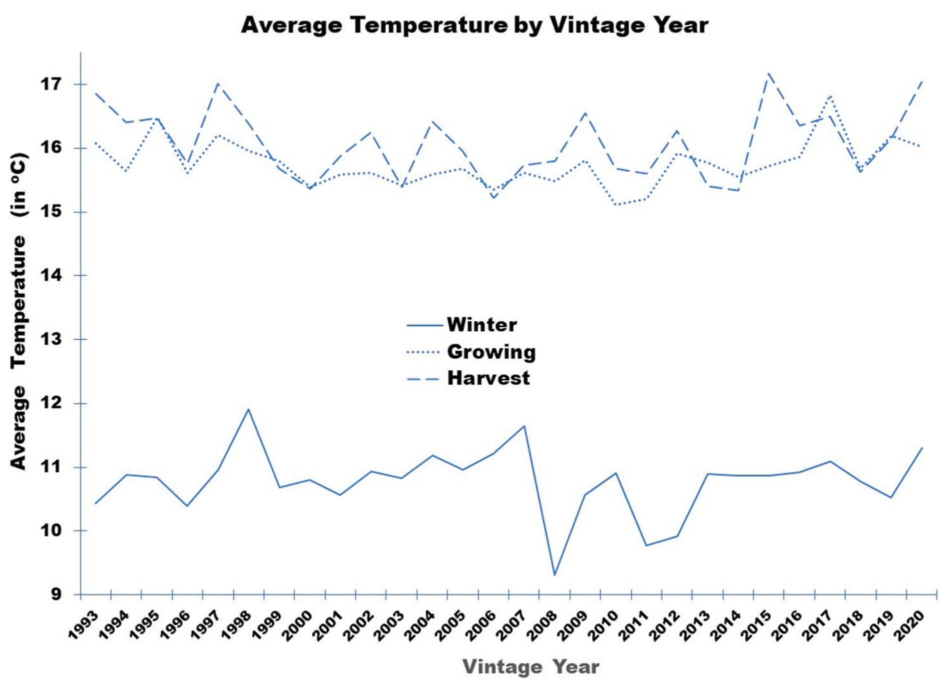

Figure 2. Seasons' average temperature by vintage year.

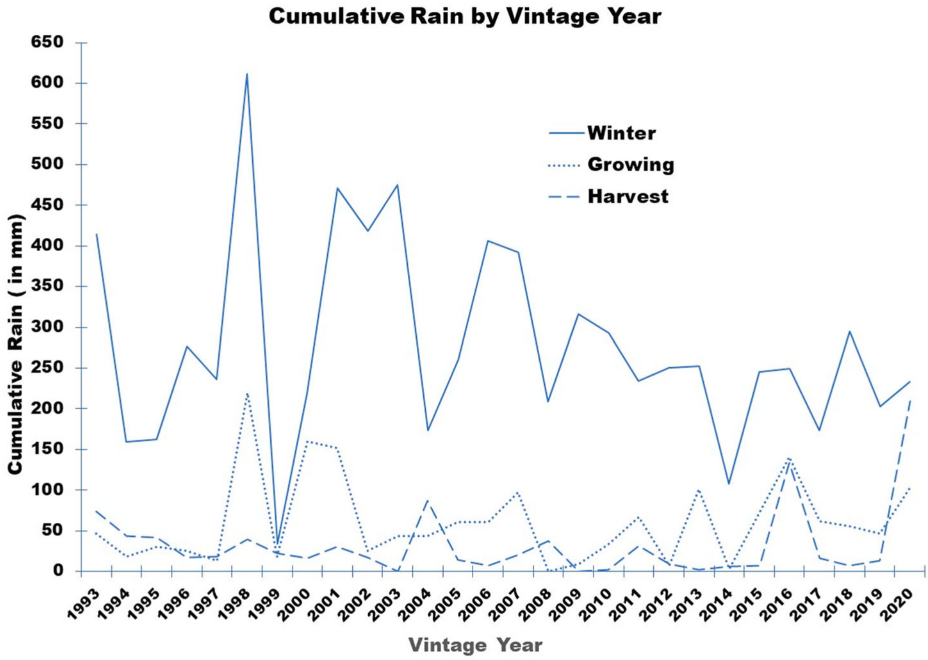

Figure 3. Seasons' cumulative rain by vintage year.

seasons in the Southern Hemisphere correspond to the following months: winter (June-August); growing season (September-February); and harvest (March-April). The vintage is defined by the harvest year. Temperatures do not exhibit any clear trend. Winter rainfall, however, does show a downward pattern.

Modeling approach

The majority of previous studies have relied on a regression model inspired by Ashenfelter's initial structure, or close variations of it. In other words, they have described the potential weather effects based on the average temperature during the growing season (and sometimes also its square), the cumulative rainfall during the period before the vintage, and occasionally the average temperature difference (maximum minus minimum) during the growing season. See, for instance, Ashenfelter (2008), Haeger and Storchmann (2006), Outreville (2018), and Oczkowski (2016a).

In this study, since we had access to more granular and richer weather data, our modeling strategy aimed at describing more fully the different weather characteristics during each season of the lifecycle of the grapevine. The structure of our model was based on the following regression scheme:

$$R_{p,q} = I + \sum_i \alpha_i W_{i,q} + \sum_j \beta_j G_{j,q} + \sum_k \gamma_k H_{k,q} + \sum_s \omega_s \Omega_{p,s} + \theta Log(Price_p) + \varepsilon_p \quad (1)$$

where R denotes the WS rating assigned to the p observation; q designates the vintage associated with the p observation; I is the intercept; the indices i, j and k refer to the different weather variables (described later) associated with each season, that is, W(inter), G(rowing) and H(arvest); α, β and γ are the regression coefficients associated with weather effects; s is the index that identifies the winery; ω and Ω denote, respectively, the winery coefficient and a dummy (1, 0) that links the p observation to the corresponding winery; θ is the coefficient associated with the price of the p observation; and ε_p is the error term.

Results and discussion

For modeling purposes, we divided the dataset in two groups: (i) white wines; and (ii) red wines. The white wines dataset consisted of two subgroups, sauvignon blanc (291 observations) and chardonnay (345 observations). The red wine dataset consisted of 317 observations, of which, 195 corresponded to pinot noir.

It should be noted that certain variables cannot be incorporated simultaneously into the model as they result in multicollinearity. Such combinations are detected by analyzing the correlation matrix. For example, the average temperature, Avg(T), in any season, is highly correlated with both Avg(T_{max}) and Avg(T_{min}). Thus, all three variables cannot be included. For the sake of clarity, we used Avg(T) which is easier to interpret and facilitates comparisons with other studies. We also included Avg(T)^2 as a variable, which is useful when dealing with quantities that exhibit local optimal values, as it has been reported by previous authors. In relation to Avg(T), we expressed it in the regression using a shift from its mean-value to minimize the possibility of collinearity (since we were also including its square as an independent variable). Note that both Max(T_{max}) and Min(T_{min}), which were included in the analyzes, exhibit low correlation with Avg(T). This is rather intuitive and expected since both Max(T_{max}) and Min(T_{min}) are determined by only one observation from the season whereas Avg(T) reflects the overall tendency over the entire season.

Perhaps surprisingly, humidity, which is obviously positively correlated with rainfall, does not exhibit the high correlation that one might have expected; typical values vary depending on the season but they were always below 35%; thus, both variables can co-exist in a model without triggering undesirable effects due to multicollinearity. It was not possible to include a dummy for each winery as we did not have enough data points. Recall that the number of wineries was 45, 50 and 52 for the reds, sauvignon blanc and chardonnay, respectively. Thus, we ranked the wineries based on the number of observations, and then grouped them using the average rating as a criterion. We ended up with six white winery groups and four red winery groups (wineries with similar ratings were assigned to the same group). The aggregate of the six white winery groups accounted for 68.5% of the observations; the aggregate of the red wine wineries, for 54.3%. Wineries not included in these groups accounted each for less than 1% of the total number of observations.

In all the analyses we considered three basic models based on the structure specified by Equation (1): (a) only weather variables; (b) weather and winery variables; and (c) weather and winery variables but adding also the natural logarithm of the price (inflation-adjusted to 2020 US$ using the U.S. CPI) as a control. Adding variables gradually to the model facilitates comparisons; it is also in agreement with the approach taken by other authors in similar studies (see, for instance, Haeger & Storchmann, 2006; Oczkowski, 2016a; Oczkowski, 2016b; Ramirez, 2008). As mentioned before, wine raters are not aware of the suggested retail price. Nevertheless, we decided to include the price as a potential explanatory variable since it might contain information not fully captured by the weather variables and only known to the producers (since they suggest the price).

Table 3. Sauvignon Blanc models ($N = 291$).

		Model 1 (Weather Only)		Model 2 (Weather and wineries)		Model 3 (Weather, wineries, and price)	
		Par. Est.	Std. Err.	Par. Est.	Std. Err.	Par. Est.	Std. Err.
	WINTER (Jun-Aug)						
α_1	Avg(T), °C	−1.192**	0.450	−1.141**	0.438	−1.361**	0.458
α_2	Min(T_{min}), °C	0.706*	0.278	0.661*	0.270	0.698*	0.280
α_3	Avg(Humidity), %	−0.127*	0.055	−0.120*	0.055	−0.134*	0.056
α_4	Cumulative SR, KW/m^2	0.013***	0.004	0.013***	0.004	0.014***	0.004
	GROWING SEASON (Sept-Feb)						
β_1	Avg(Humidity), %	−0.188**	0.058	−0.181**	0.058	−0.182**	0.060
	HARVEST (Mar-Apr)						
γ_1	Avg(T), °C	−1.493**	0.522	−1.357**	0.523	−1.402**	0.519
γ_2	Avg(T)^2, °C	−0.694	0.644	−0.691	0.634	−0.752	0.634
γ_3	Max (T_{max}), °C	0.363*	0.184	0.348†	0.184	0.356†	0.183
	WINERIES						
ω_1	Winery-1			1.789***	0.391	1.198**	0.374
ω_2	Winery-2			0.693*	0.330	0.866**	0.321
ω_3	Winery-3			−0.274	0.471	−0.412	0.472
ω_4	Winery-4			1.262**	0.486	1.049*	0.437
ω_5	Winery-5			0.352	0.413	0.143	0.411
ω_6	Winery-6			1.792***	0.428	1.431**	0.435
	PRICE						
θ	Log (Price)					1.946***	0.439
	Constant (I)	112.377***	9.857	110.554***	9.755	108.360***	10.156
	adj-R^2	0.107		0.179		0.234	

†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Sauvignon blanc

Table 3 describes the relevant variables and the results (heteroscedasticity consistent) obtained with each of the three models. The coefficients are consistent in all three models (same signs and similar numerical values), which attests to the robustness of the estimates (model stability). The adj-R^2 of model 1 (only weather) is 0.11; adding the wineries (model 2) raises the adj-R^2 to 0.18; and adding the price (model 3) yields an adj-R$^2 = 0.23$. Not shown in the table are the results of a winery-only model (adj-R$^2 =$ 0.09) and a model based only the price (adj-R$^2 = 0.07$). These results suggest that the weather effects are not sufficient to explain the ratings (actually, rating variations) and that winery matters. Winery effects, of course, could be due to a number of things, e.g. the way the grapes are harvested (manually or by mechanical means); the type of container used during fermentation (for example, oak, steel, plastic, etc.); or even the specific phenolic composition of the soil which can be quite different even for parcels located in the same general area (Urvieta et al., 2021). Unfortunately, we do not have information that would allow us to elaborate more on this point.

The 0.11 adj-R^2 achieved by the weather-only model might seem low. However, it is somewhat consistent with results from previous research. For example, Oczkowski (2016a) reported a value of 0.08 in his study of Australian sauvignon blanc when he employed a weather-only model (albeit with different weather variables). And the same author in a different study based on a mix of red and white Australian wines reported an adj-R$^2 = 0.03$, which improved to 0.34 when adding winery effects (Oczkowski, 2016b).

Table 4. Chardonnay models ($N = 345$).

		Model 1 (Weather Only)		Model 2 (Weather and wineries)		Model 3 (Weather, wineries, and price)	
		Par. Est.	Std. Err.	Par. Est.	Std. Err.	Par. Est.	Std. Err.
	WINTER (Jun-Aug)						
α_1	Avg(T), °C	−2.292***	0.559	−2.284***	0.556	−2.595***	0.545
α_2	Min(T_{min}), °C	1.326***	0.324	1.229***	0.311	1.373***	0.298
α_3	Avg Humidity, %	−0.195*	0.070	−0.083	0.066	−0.121*	0.060
α_4	Cumulative SR, KW/m^2	0.010**	0.005	0.014**	0.005	0.015**	0.004
	GROWING SEASON (Sept-Feb)						
β_1	Avg(Humidity), %	−0.145	0.112	−0.070	0.106	−0.097	0.099
	HARVEST (Mar-Apr)						
γ_1	Avg(T), °C	−1.001†	0.518	−0.603	0.469	−0.728†	0.436
γ_2	Avg(T)^2, °C	−1.204†	0.667	−1.720**	0.601	−1.736**	0.582
γ_3	Max(T_{max}), °C	0.404†	0.218	0.338†	0.193	0.345†	0.182
	WINERIES						
ω_1	Winery-1			2.449***	0.603	1.945**	0.618
ω_2	Winery-2			2.255***	0.439	2.589***	0.434
ω_3	Winery-3			1.881***	0.504	1.832***	0.506
ω_4	Winery-4			3.312***	0.484	2.359***	0.539
ω_5	Winery-5			1.043†	0.548	1.011†	0.527
ω_6	Winery-6			3.858***	0.486	3.266***	0.500
	PRICE						
θ	Log(Price)					2.483***	0.515
	Constant (I)	112.377***	9.857	109.783***	15.937	111.095***	15.406
	adj-R^2	0.117		0.268		0.336	

†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Chardonnay

The same comments regarding the stability of coefficients observed for sauvignon blanc variety apply here (see models 1, 2 and 3 in Table 4). The adj-R^2 of model 1 (only weather) is 0.12; adding the wineries to weather effects (model 2) raises the adj-R^2 to 0.27; and including the price (model 3) yields an adj-$R^2 = 0.34$. Not shown in the table are the results of a winery-only model (adj-$R^2 = 0.16$). Again, these results suggest that the weather effects are not sufficient to explain the ratings and that in this case wineries are a bit more important than in the case of the sauvignon blanc. Similarly, a model using only the price as an independent variable resulted in an adj-$R^2 = 0.07$. Note that the negative sign in the case of Avg(T)^2 during the harvest is indicative of an inverted parabola, which suggests that there is an optimal value for the Avg(T) somewhere between 15.2 °C and 17.2°C, the minimum and maximum Avg(T) values observed during the season (see Table 2).

As before, the 0.12 adj-R^2 achieved by the weather-only model might seem low. But it is also consistent with the result obtained by Oczkowski (2016a), who reported a value of 0.10 in his study of Australian chardonnay.

Elasticities

In general, it is difficult just looking at the regression coefficients to identify which weather variables have the most influence on the ratings. The reason is that the different coefficients are associated with variables which are expressed in different units, and whose order of magnitude is substantially uneven. For instance, a winter average temperature could be around 10 °C, whereas the solar radiation could of the order of 200 KW/m^2. Hence, it is more illustrative to estimate the corresponding elasticities for each variable. The elasticity refers to how much a 1% variation in a given variable will impact (percentage wise) the value of the rating. If x denotes a generic weather variable, and R denotes the rating, it follows from Equation (1) that by computing ∂R/∂x we can estimate the corresponding elasticity. Briefly,

$$\left(\frac{\Delta R}{R}\right) \approx \left(\frac{\partial R}{\partial x}\right)\left(\frac{\hat{x}}{\hat{R}}\right)\left(\frac{\Delta x}{x}\right) \tag{2}$$

where $\hat{x}$ and $\hat{R}$ denote the average or representative values within the range of interest, and (ΔR/R) and (Δx/x) refer to percentage changes. Clearly, ∂R/∂x can only be estimated for continuous variables. Table 5 shows the elasticities based on the model coefficients shown in Tables 3 and 4, in the case of white wines. They are only calculated when the relevant coefficients are significant. These elasticities were estimated with the value of the coefficients obtained with model 3 (similar values were obtained with either model 1 or 2).

The results are quite clear. In the case of sauvignon blanc the most influential weather variable is the Avg(T) during harvest. The negative sign associated with this elasticity indicates that any increase over 16.1 °C (the average value; see Table 2) will have a negative effect on the rating. The importance of humidity during both, winter and the growing season, is also noticeable; the negative values are in agreement with the empirical evidence which indicates that excessive rainfall is detrimental to wine quality. Finally, the negative sign associated with Avg(T) during winter might seem counterintuitive, but in conjunction with the fact that the sign of Min(T_{min}) is positive seems to indicate that large temperature variations are undesirable, an effect also known to winemakers. What is more interesting about the model is that it emphasizes the importance of the weather during winter, and the relevance of the humidity. This is in clear contrast with previous models based on French, Californian and Australian wines in which in general the average temperature during the growing season played the leading role (Ashenfelter, 2008; Oczkowski, 2016a; Oczkowski, 2016b; Outreville, 2018; Ramirez, 2008).

Table 5. Elasticities: Sauvignon Blanc, Chardonnay, and red wines

Weather variables	Sauvignon Blanc Elasticities	Chardonnay Elasticities	Red Wines Elasticities
WINTER (Jun-Aug)			
Avg(T),	−0.169	−0.326	–
Max(T_{max}), °C	–	–	−0.229
Min(T_{min}), °C	0.007	0.014	0.012
Avg(Humidity), %	−0.139	−0.128	−0.612
Cumulative SR, KW/m^2	0.029	0.030	–
Cumulative Rain, mm	–	–	−0.020
GROWING SEASON (Sept-Feb)			
Avg(T), °C	–	–	−1.072
Max(T_{max}), °C	–	–	0.260
Avg(Humidity), %	−0.166	−0.089	−0.566
HARVEST (Mar-Apr)			
Avg(T), °C	−0.260	−0.130	–
Max(T_{max}), °C	0.111	0.107	0.233

In reference to the chardonnay, the elasticities reported in Table 5 are in broad agreement with those estimated for the sauvignon blanc, except for the effect of the Avg(T) which is much stronger in winter and weakier during harvest. Also, the overall importance of winter weather, already detected in the sauvignon blanc analysis, is manifest here. Finally, it is worth mentioning the relevance of solar radiation during winter, whose elasticity is similar for both white wines. True, this effect is small compared to that of other weather variables, but it is nevertheless significant. This variable has not been considered in most previous weather-wine quality studies.

Red wines

Table 6 shows the relevant variables and the results (heteroscedasticity consistent). The regression coefficients, in the first three models, display the same stability reported previously in relation to the white wines. Table 5 reports the corresponding elasticities.

The most salient fact in this case is that the weather matters a lot more than in the case of the white wines. More specifically, the adj-R^2 of the weather-only model is 0.22. (The price is also is more relevant, relatively speaking, as the price-only model yields an adj-$R^2 = 0.19$.) The higher relative importance of the weather is also manifest in the overall higher elasticity values compared to those of the white wine models. Similar to the white wines results, humidity in both, the growing season and winter, plays an influential role. Also, analogous to the chardonnay findings, we detect the existence of an optimal value for the Avg(T), during harvest, around 16.1°C (recall that the Avg(T) in the regression is incorporated via a shift with respect to its mean, in this case, 16.1°C, and the sign of the coefficient of $[\text{Avg(T)}-16.1]^2$ is negative). The negative value associated with the Avg(T)

Table 6. Red wines ($N = 345$) models and Pinot Noir ($N = 195$) model.

		Model 1 (Weather Only)		Model 2 (Weather and wineries)		Model 3 (Weather, wineries, and log of price)		Pinot Noir Model (Weather, wineries, and price)	
		Par. Est.	Std. Err.	Par. Est.	Std. Err.	Par. Est.	Std. Err.	Par. Est.	Std. Err.
	WINTER (Jun-Aug)								
α_1	$\text{Max}(T_{max})$, °C	−0.941***	0.216	−0.784***	0.209	−0.898***	0.183	−1.018***	0.253
α_2	$\text{Min}(T_{min})$, °C	1.247***	0.369	1.213***	0.343	1.262***	0.337	1.581**	0.517
α_3	Avg (Humidity), %	−0.696***	0.140	−0.537***	0.139	−0.589***	0.122	−0.739***	0.153
α_4	Cum. Rain, mm	−0.007*	0.003	−0.008*	0.003	−0.006*	0.002	−0.003	0.004
	GROWING SEASON (Sept-Feb)								
β_1	Avg(T), °C	−5.641***	1.183	−5.595***	1.111	−5.931***	1.097	−7.712***	1.626
β_2	$\text{Max}(T_{max})$, °C	0.903*	0.371	0.698*	0.345	0.799**	0.298	1.496***	0.372
β_3	Avg (Humidity), %	−0.624**	0.205	−0.539**	0.196	−0.622***	0.170	−0.855***	0.244
	HARVEST (Mar-Apr)								
γ_1	Avg(T)^2, °C	−2.352*	0.964	−2.466**	0.873	−2.504**	0.867	−3.229**	1.202
γ_2	$\text{Max}(T_{max})$, °C	0.805***	0.216	0.764***	0.197	0.747***	0.188	0.876**	0.270
	WINERIES								
ω_1	Winery-A			3.523***	0.310	2.719***	0.294	2.164***	0.326
ω_2	Winery-B			1.321**	0.494	2.235***	0.429	2.219***	0.508
ω_3	Winery-C			1.427**	0.505	2.343***	0.421	1.872**	0.571
ω_4	Winery-D			1.516*	0.659	1.118†	0.603	1.838**	0.656
	PRICE								
θ	Log(Price)					3.228***	0.345	3.223***	0.423
	Constant (I)	261.441***	35.903	242.227***	34.786	248.103***	31.367	286.679***	46.390
	adj-R^2	0.217		0.359		0.503		0.509	

†$p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

during the growing season, combined with the positive value associated with Max(T_{max}), might seem puzzling. However, we think this is just evidence of the complex interplay between the average and maximum temperatures when the temperature range is narrow and well within the adequate limits for wine production. (Recall that during the growing season the average temperature fluctuated between 15.1°C and 16.8°C, while Max(T_{max}) fluctuated between 24.4°C and 30.3°C, that is, fairly stable boundaries, as indicated in Table 2). Additionally, it is clear that the weather in the growing season in this case plays a much more influential role compared to the case of white wines, in which only the humidity during the growing season was significant. The importance of the Avg(T) during the growing season is apparent from its elasticity (−1.072), which exceeds by far, in absolute value, all the other elasticities (see Table 5). This finding is in agreement with the findings of previous studies focused on red wines (Ashenfelter, 2008; Oczkowski, 2016a; Oczkowski, 2016b; Outreville, 2018; Ramirez, 2008).

Finally, we also tested a model with all effects (weather, wineries and price) but with a reduced dataset, that is, considering only the pinot noirs (195 observations). The results shown in the rightmost columns in Table 6 are very similar to those obtained with the full red wine dataset (model 3).

The trend variable

Many authors have employed models with a similar structure to the model shown in Equation (1), but with a minor modification: they incorporate what they call a 'trend variable.' In essence, they add to the model a constant multiplied by Y, in which Y is the year (vintage). The motivation is to control for, allegedly, improvements in technology (e.g. increasing know-how, more experience) as time goes by, which in turn, might impact quality (and thus, ratings) positively and also improve the model explanatory power. See, for instance, Haeger and Storchmann (2006) or Oczkowski (2016b). The example provided by Oczkowski is illustrative. His weather-only model, based on Australian premium wines data, resulted in an adj-$R^2 = 0.03$; after adding the trend variable it increased to 0.06.

Our concern with this technique is that the trend variable (vintage) is normally highly correlated with the weather variables. After all, and not surprisingly, vintages are defined by their weather characteristics. Hence, adding the trend variable typically makes many significant weather variables not-significant and contributes substantially to variance inflation, which, in turn, makes the coefficient estimates unreliable. In the case of Oczkowski's example, we do not know if adding the trend variable contributed to variance inflation as it was not reported. However, in our case, the red wine example is telling. The initial weather-only model resulted (as already reported) in an adj-$R^2 = 0.22$ with all nine variables achieving significance and no variance inflation issues (VIF coefficients all below 3.80, noting that 5 is usually considered an acceptable limit). Adding the trend variable increased the adj-R^2 to 0.24 (a negligible improvement) but at the expense of rendering six weather variables not-significant and increasing the VIF coefficients to uncomfortable levels (four values higher than 5, and two very close to 10). A similar situation was detected when adding the trend variable to the weather-only white models: negligible adj-R^2 improvements coupled with variance inflation. This is the reason we decided not include a trend variable in our models.

Regrettably, past researchers have failed to acknowledge this potential shortcoming when adding the trend variable, and have not reported the variance inflation metrics when doing so, or, alternatively, reported whether they have employed any technique to mitigate this phenomenon. This makes it difficult to interpret their results. Hence, we remain skeptical about the merits of adding this variable.

Humidity and solar radiation

The vast majority of previous studies, as already mentioned, have relied on models based only on temperature-and-rainfall weather variables. One could be skeptical about the added benefit of including humidity and solar radiation as independent variables. Recall that our previous weather-only models resulted in adj-$R^2 = 0.11$, 0.12, and 0.22 for the sauvignon blanc, chardonnay and red wines cases, respectively. Therefore, a reasonable exercise is to eliminate from these models the humidity and solar radiation and run the regression with only temperature-and-rainfall weather variables. The resulting adj-R^2 were 0.04, 0.10, and 0.13 respectively. In short, in the case of the chardonnay the deterioration in adj-R^2 was minor (0.10 versus 0.12). However, for the sauvignon blanc (0.04 versus 0.11) and red wines (0.13 versus 0.22) the deterioration in the capacity of the models to explain the variance was substantial. Clearly, not including humidity and solar radiation in weather-wine quality analyses can lead to underestimate the importance of the weather on wine quality. The relevance of humidity and solar radiation effects on wine quality are in agreement with the findings of Cuneo et al. (2013), notwithstanding the different objective of their study. They concluded that the anthocyanin profile of the Casablanca wines, a factor that affects wine quality, was determined among other things by climate variables such as relative humidity, solar radiation and wind speed.

Given the uniqueness of the climate in the Casablanca Valley it would be unwise to conclude that not including humidity and solar radiation when modeling the weather in other locations can have detrimental effects. Nevertheless, the case for exploring the use of more weather variables, especially in those instances in which the initial adj-R^2 is low, as in the examples reported by Ramirez (2008) or Oczkowski (2016b), seems justified. Again, the following example is telling. We ran the regression on the sauvignon blanc, chardonnay and red wines datasets using the same variables employed by Oczkowski in his analyses of Australian wines, namely, Avg(T) and Avg$(T)^2$ during the growing season, rainfall during harvest, and Avg$(T_{max} - T_{min})$ during the growing season, (Oczkowski, 2016b). The resulting adj-R^2 were 0.01, 0.00 and −0.01, respectively. Thus, one is left to wonder whether in the Australian study the adj-R^2 could have been higher if an enhanced set of weather variables had been employed.

To summarize, in instances in which a model based only on temperature-and-rainfall variables results in a low adj-R^2, it seems prudent to explore the benefits of including additional weather variables, and to focus not only on the growing season.

Is the Casablanca Valley unique?

Ramirez asked himself that very same question in relation to California's Napa Valley (Ramirez, 2008). He concluded that Napa was indeed very much like other wine regions, although in fairness he based his statement exclusively on a comparison with the French wine regions. In our case, a positive response is warranted: Casablanca does seem unique, at least from the perspective of the relationship between weather and wine quality.

Yes, weather affects wine quality in Casablanca, along with wineries; in that sense Casablanca is not different than other regions. However, the importance of both, humidity and solar radiation, the relevance of winter (along with the growing season), and the necessity to include variables such as Max(T_{max}) and Min(T_{min}), that is, maximum and minimum absolute values, makes Casablanca special.

Conclusions

The previous analyses suggest several conclusions:

(1) The weather has an important effect on the quality of Casablanca wines and it is much more pronounced in the case of red wines than white wines. The nature of this effect seems to be quite different compared to what has been observed in other regions, namely, winter weather matters, and also humidity and solar radiation play an important role. In short, the relationship between weather and wine quality is driven by parameters that differ from those behind the quality of Californian, French, and Australian wines. This finding seems to be consistent with the uniqueness of Casablanca climate (Csc), whose cold summers are an anomaly among global winery regions. However, the explanatory power of weather variables in relation to wine ratings in Casablanca seems to be more in line with what has been observed in relation to Australian and California wines than European wines.

(2) Given the uniqueness of Casablanca climate, we should refrain from extending our conclusions to other wine regions unguardedly. Yet, it seems prudent in future weather-wine quality research to at least explore the benefits of incorporating additional weather variables. This is especially encouraged in those cases in which a weather-only model (based on temperature and rainfall) yields very low adj-R2.

(3) It follows from the relevance of the wineries in explaining wine quality, that the idea of investigating the differences in technology, soil composition and other factors that might account for this effect seems warranted. Clearly, this is a topic beyond the scope of this study, but it deserves further attention.

(4) The potential benefits of including in these models the trend variable seems to have been oversold. Unless enough information regarding variance inflation is reported (either that there was none, or alternatively, there was but its effects were mitigated by means of ridge regression or other techniques) one should exercise caution when interpreting these results.

(5) We hope to encourage future researchers to report the corresponding elasticities in their weather-wine quality studies. Not having this information, particularly in cases in which the average value of the weather variables is not reported, makes it difficult to identify the most influential variables.

Note

1. Knowles (2002) and Morel-Astorga (2001) provide a very thorough account of the evolution of the wine-makingindustry in Chile. This paragraph is largely based on their texts.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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