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Research Article

Winegrape Yield and Revenue Variability in Australia

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While winegrowers usually want to achieve consistent yield targets, there is a high degree of yield and price (and hence gross revenue) variability in winegrape production. The aim of this study was to determine whether there are differences in yield and revenue variability across climates, varieties, and regions in Australia. This was performed by estimating statistical models of the impact of these three variables on the coefficient of variation of yield and gross revenue per hectare. The results suggest that hotter and drier regions exhibit lower interannual yield variability, something that in the past may have been largely explained by the use of irrigation, but which may change in the future with climate change and higher water prices. The results also showed that there are sometimes differences in yield and revenue variability, not only across regions, but also between varieties.

1. Introduction

Winegrowers appreciate low year-to-year variations in grape yields. Yield variations are sometimes caused by extreme events such as droughts [1] or high unexpected pest pressures [2]. However, yield variability is mostly influenced by vine management and weather differences across seasons [3]. Growers often change their vineyard management strategies to achieve more consistent yields and thereby more consistent revenues. Yet, further research is needed to better understand winegrape yield variability and to develop techniques for stabilising yields [4]. This knowledge is increasingly important because obtaining consistent yields is becoming more difficult with climate change [5].

The aim of this study was to determine whether there are differences in yield and revenue variability across climates, varieties, and regions in Australia. Coefficients of variation (CoV) were computed for different variety-by-region combinations over the 2001-23 period, which were then regressed on different variables. In doing so, insights into overall yield and revenue variability throughout those years could be provided. While some of the possible reasons explaining yield and revenue variability will be discussed, this study did not intend to provide a causal link between the explanatory variables used in the models developed and yield or revenue variability. The study also did not seek to identify the variables influencing yield in a given season, for which process-based models (e.g., Leolini et al. [6]) or panel data models (e.g., Puga et al. [7]) may be more suitable.

2. Materials and Methods

2.1. Data. A new dataset developed by Anderson and Puga [8] provides time series on area, production, and price by variety and region, as well as many other variables and indexes. These data are based on various sources including the Australian Bureau of Statistics and Wine Australia, as well as Vinehealth Australia for South Australia. Anderson and Puga [9] provide a detailed explanation of the sources and assumptions used in the compilation of that dataset. An updated summary of those sources and assumptions is provided in Note 1 of the Supplementary Information.

These data were used to calculate the CoV of yield (i.e., production per hectare) and gross revenue per hectare (revenue, hereafter). While variability in costs of production also is highly relevant, cost data by region and variety are unavailable to match the comprehensive yield and gross revenue data available. Revenues were calculated using real prices adjusted for inflation based on the Consumer Price Index (CPI) for the June quarter of each year, providing real values in 2023 Australian dollars. The CoV was calculated as the ratio of the standard deviation to the mean. It therefore provided a meaningful indicator to compare the degree of variation between varieties, regions, or variety-by-region combinations even though the means are very different. For calculating the CoV, data from 2001 to 2023 were used, after excluding the data for unidentified varieties. Table 1 shows the CoV values for the regions and varieties with the largest shares of area.

Climate data on growing season average temperature (GST) and growing season precipitation (GSP) from Anderson and Puga [8] were also used for the study. GST is one of the most-used climate indexes to represent temperature in viticulture [10, 11], and GSP is another commonly used index that has a high correlation with other precipitation-related variables [12].

2.2. Statistical Models. With the main objective of uncovering the extent to which yield variability differs across regions with different GST and GSP, the following model was estimated:

$$\ln\_\mathrm{CoV}\_\mathrm{Yield}_{v,r} = \alpha + \beta_1 \mathrm{GST}_r + \beta_2 \mathrm{GSP}_r + \varphi_v + \theta \ln\_\mathrm{area}_{v,r} + \varepsilon_{v,r}. \quad (1)$$

The dependent variable is the natural logarithm of the coefficient of variation of yield of variety v in region r, across all the years for which there are data available for that variety in that region. The main variables of interest in this model are the regional GST and GSP, of which β_1 and β_2 are their respective coefficients. The natural logarithm of the average area of variety v in region r across the time period $\ln\_\mathrm{area}_{v,r}$ serves as a control variable, and θ is its coefficient. The model also includes variety dummy variables (φ_v) that control for differences in the CoV across varieties. The term α is a constant and $\varepsilon_{v,r}$ is the error term.

With the same objective but for analysing revenue variability, the following model was also estimated:

$$\ln\_\mathrm{CoV}\_\mathrm{Revenue}\_\mathrm{per}\_\mathrm{ha}_{v,r} = \alpha + \beta_1 \mathrm{GST}_r + \beta_2 \mathrm{GSP}_r + \varphi_v + \theta \ln\_\mathrm{area}_{v,r} + \varepsilon_{v,r}. \quad (2)$$

The difference between models (1) and (2) is the dependent variable, which in this case is the natural logarithm of the coefficient of variation of revenue per ha of variety v in region r, also across all the years for which there are data available for that variety in that region.

In addition to model (1), another model was estimated, in which the dependent variable is again the natural logarithm of the coefficient of variation of yield given as

$$\ln\_\mathrm{CoV}\_\mathrm{Yield}_{v,r} = \alpha + \varphi_v + \gamma_r + \theta \ln\_\mathrm{area}_{v,r} + \varepsilon_{v,r}. \quad (3)$$

The difference between model (3) and model (1) is that model (3) includes region dummy variables (γ_r) instead of GST and GSP. These region dummies aimed to capture all time-invariant observable and unobservable characteristics of each region, including their climate. While the climate of the regions might have changed between 2001 and 2023, we consider climate as a region-specific characteristic. That is the reason why the region dummies aim to capture, among other variables, the region's GST and GSP. While including GST and GSP is possible in models such as (3), however, it leads to massive issues of multicollinearity, as evidenced by the variance inflated factors (VIFs) of the independent variables of a model of that type (results discussed in Note 2 of the Supplementary Information). Therefore, by indirectly controlling for more region-specific characteristics, the coefficients of the variety dummies are more reliable than those of the model (1). At the same time, the region dummies in this model also provided information on differences in yield variability across regions.

The climate variables in models (1) and (2) are in levels. While using the natural logarithms is possible, using levels leads to a straightforward interpretation in which a unit increase in GST or GSP can be associated with a certain percentage change in the CoV of yield or revenue. Moreover, specifying climate variables in levels is a standard practice in the literature, as using logs can sometimes lead to misinterpretation issues [13].

A similar model to (3) was also estimated, but in this case only to analyse revenue variability, so the dependent variable is the same as in model (2):

$$\ln\_\mathrm{CoV}\_\mathrm{Revenue}\_\mathrm{per}\_\mathrm{ha}_{v,r} = \alpha + \varphi_v + \gamma_r + \theta \ln\_\mathrm{area}_{v,r} + \varepsilon_{v,r}. \quad (4)$$

There was a two-fold justification for the use of the natural logarithm of CoV as opposed to CoV in models (1) to (4). First, this specification led to a more straightforward interpretation of the coefficients: it was easier to analyse proportional changes in the CoVs than changes in the CoVs

Table 1: Yield, revenue per ha, coefficients of variation (CoV), and climate variables for the regions and varieties with a bearing area higher than 2,000 ha in 2023.

	Area (ha)	Yield (t/ha)	Revenue/ha (AUD)	CoV yield	CoV revenue (ha)	GST (°C)	GSP (mm)
Region							
Riverland	19850	22.0	12601	0.63	0.83	22.0	131
Riverina	17108	14.8	7837	0.68	0.72	22.6	237
Barossa Valley	11445	6.2	9994	0.60	0.75	18.8	218
Murray Darling-Swan Hill (vic)	8722	19.0	12248	1.67	1.63	22.0	160
McLaren Vale	7160	7.0	13953	1.27	1.46	19.6	199
Murray Darling-Swan Hill (NSW)	6992	21.3	12974	1.14	1.07	22.4	154
Langhorne Creek	5864	10.8	16990	1.43	2.05	19.8	173
Margaret River	5592	4.9	9981	0.85	0.60	19.6	229
Coonawarra	5479	7.6	11247	0.69	0.81	16.9	283
Clare Valley	4973	4.7	7866	0.50	0.65	19.4	223
Padthaway	3608	9.5	13887	0.62	0.78	18.6	194
Adelaide Hills	3607	6.4	13378	0.79	0.95	17.8	293
Hunter Valley	2622	4.1	6473	1.13	0.86	22.3	565
Wrattonbully	2617	11.3	16656	0.69	0.92	18.3	220
Yarra Valley	2478	5.0	11400	0.84	0.57	17.6	531
Great Southern	2415	3.8	7203	1.00	0.71	18.3	344
Eden Valley	2195	5.0	9852	0.60	0.77	18.6	214
Tasmania	2069	5.3	19476	0.76	0.51	15.1	323
Variety							
Syrah	43280	6.0	9891	0.98	0.80	19.2	322
Cabernet Sauvignon	26441	6.2	9598	1.46	1.26	19.3	322
Chardonnay	21512	7.1	11064	0.93	0.81	19.2	322
Merlot	8163	6.7	10112	1.07	0.89	19.2	315
Sauvignon Blanc	6462	8.7	13938	1.20	1.04	19.1	310
Pinot Noir	6029	7.1	12733	1.49	1.57	19.2	320
Pinot Gris	4892	11.2	19730	3.59	2.94	18.9	331
Sémillon	3800	9.3	11721	0.96	0.78	19.3	316
Riesling	3179	7.3	11400	2.12	1.88	19.0	309

Average yield and revenue per ha and coefficients of variation (CoV) based on data from 2001 to 2023. GST is the growing season average temperature and GSP is the growing season precipitation.

themselves. Second, using the natural logarithm of the dependent variable could help mitigate issues of heteroskedasticity and deal with outlying or extreme values by narrowing the range of the variable [14].

The CoV of both yield and revenue per ha was expected to be smaller for those variety-by-region combinations with larger areas, which was the reason behind the inclusion of $\ln\_area_{v,r}$ as a control variable in models (1) to (4). The intuition in the inclusion of this control variable is that larger areas are correlated with more vineyards or growers, and we expect a lower standard deviation of yield or revenue with a greater number of vineyards or growers. From a statistical viewpoint, this relates to the law of large numbers. Since this control variable and the dependent variable in each model were in natural logarithms, the θ coefficients were easy-to-interpret elasticities. These specifications look accurate based on a visual analysis of the plots in Figure 1. These relationships were less smooth and evident when graphing each CoV against the area, as opposed to their natural logarithms.

Models (1) to (4) could be straightforwardly estimated using standard ordinary least squares (OLS) commands if $\varepsilon_{v,r} \sim (N, \sigma^2)$. However, each observation does not represent a hectare, but rather an average over a number of hectares for each variety in a given region. As such, it was assumed that $\varepsilon_{v,r} \sim (N, \sigma^2/\omega_{v,r})$, where the $\omega_{v,r}$ are analytic weights. The analytic weights were set to be the average area across the time period for each variety-by-region combination.

In addition to estimating these models using analytical weights, the sandwich estimator of variance for obtaining robust standard errors for models (3) and (4) was applied. For models (1) and (2), since GST and GSP are region-specific variables, standard errors that allowed for intragroup correlation were specified using the clustered sandwich estimator so that these standard errors were clustered at the regional level.

3. Results

Table 2 shows the estimation results of models (1) and (2). Model (1) was observed to fit the data well, explaining 65% of the variation in the natural logarithm of the CoV of yield. By contrast, model (2) explained less than half (28%) of the variation in its dependent variable compared with model (1). As expected, the coefficients of the natural logarithm of the area in both models were negative and statistically significant, consistent with what was observed in Figure 1.

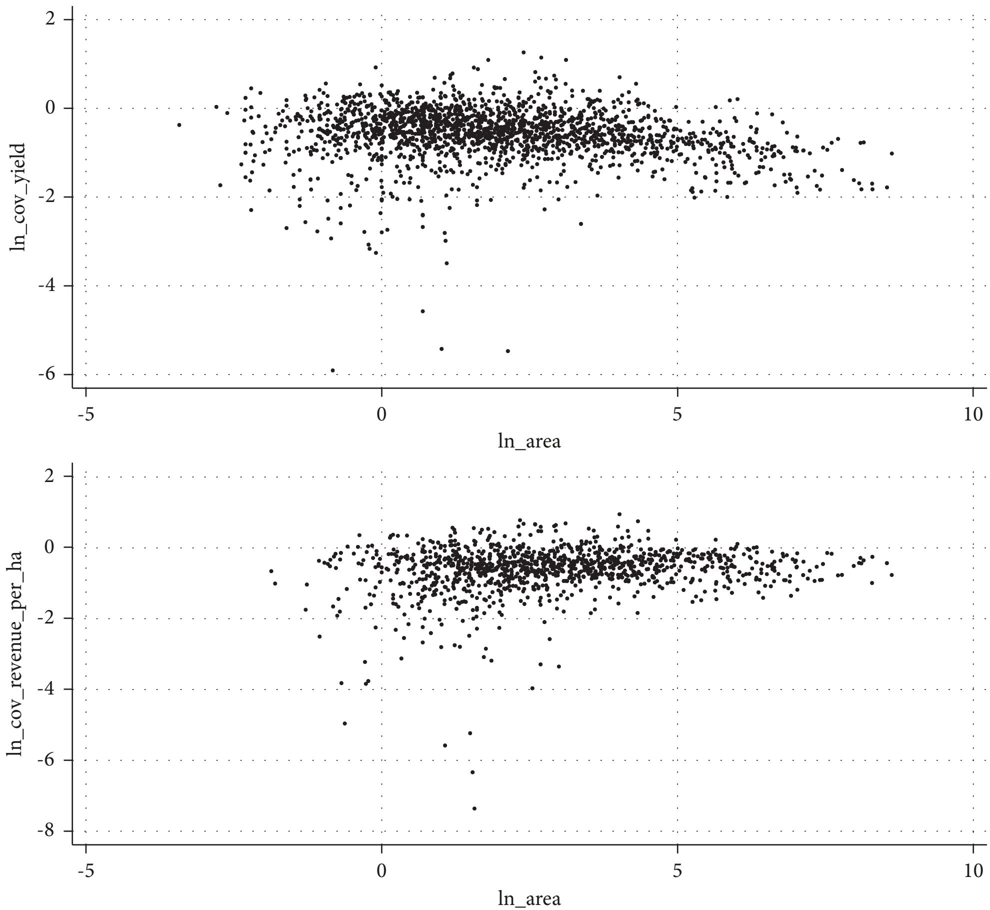

Figure 1: Scatterplots showing each observation as a function of the natural logarithm of its coefficient of variation and the natural logarithm of its area.

Table 2: Estimation results for models (1) and (2).

Model →	(1)		(2)	
Dependent variable →	ln_CoV_yield		ln_CoV_revenue (ha)	
Independent variable ↓	Coeff	SE	Coeff	SE
GST (°C)	−0.086***	0.027	−0.031	0.029
GSP (mm)	0.001*	0.001	−0.000	0.000
Variety dummy variables	Yes		Yes	
Region dummy variables	No		No	
ln_area	−0.171***	0.023	−0.049*	0.057
Constant	1.656**	0.681	0.457	0.488
R^2	0.651		0.281	

The dependent variables of models (1) and (2) are the natural logarithm of the coefficient of variation of yield and the natural logarithm of the coefficient of variation of revenue per ha, respectively. GST is the growing season average temperature and GSP is the growing season precipitation. "Coeff" stands for coefficient and "SE" for robust standard errors. Statistical significance levels: *** = 1%, ** = 5%, and * = 10%.

The coefficients of GST and GSP in model (1) were statistically significant. The interpretation of the GST coefficient was that a 1°C higher GST was associated with an 8.2% lower CoV of yield (calculated as follows: (EXP (coefficient) − 1) ∗ 100). The interpretation of the GSP coefficient is that a 10 mm higher GSP is associated with a 1.1% increase in the CoV of yield. Unlike the coefficients of GST and GSP in model (1), these coefficients in model (2) were not statistically significant.

Table 3 shows the results of models (3) and (4). The coefficients and standard errors of the natural logarithm of the area in both models were similar to those obtained in models (1) and (2), but the coefficients of determination (R^2) were higher than for models (1) and (2). Specifically, models (3) and (4) explained, respectively, 83% and 61% of the variation in the dependent variable. These higher coefficients of determination were expected because models (3) and (4) incorporated region dummy variables that

Table 3: Estimation results for models (3) and (4).

Model →	(3)		(4)	
Dependent variable →	ln_CoV_yield		ln_CoV_revenue (ha)	
Independent variable ↓	Coeff	SE	Coeff	SE
Afus Ali	0.823**	0.390	−1.055***	0.087
Arneis	−0.662***	0.139	−0.703***	0.117
Barbera	−0.228*	0.127	−0.248	0.158
Cabernet Franc	−0.060	0.074	0.009	0.100
Cabernet Sauvignon	−0.019	0.032	0.016	0.026
Canada Muscat	−0.587***	0.090		
Cayetana Blanca	−0.383	0.411	−0.087	0.137
Chardonnay	−0.135***	0.029	0.216***	0.047
Chenin Blanc	−0.133	0.138	−0.108	0.149
Colombard	−0.264***	0.047	−0.161*	0.092
Crouchen	−0.047	0.100	−0.114	0.070
Côt	−0.129	0.091	−0.165	0.105
Dolcetto	0.009	0.140	−2.291***	0.449
Durif	−0.116	0.161	−0.295***	0.101
Fiano	−0.183	0.296	−0.106	0.330
Garnacha Tinta	−0.157**	0.079	−0.271***	0.086
Gewürztraminer	−0.167**	0.072	−0.084	0.106
Graciano	−1.419***	0.364	−0.639	0.543
Grüner Veltliner	−0.664***	0.076	−0.679***	0.093
Korinthiaki	0.962***	0.354		
Lagrein	−0.248***	0.093	−0.593***	0.088
Marsanne	−0.117	0.195	−0.182	0.174
Mazuelo	0.604***	0.106		
Merlot	−0.231***	0.043	−0.057	0.055
Monastrell	−0.014	0.266	−0.172	0.230
Montepulciano	−0.367	0.282	−0.541**	0.237
Muscadelle	0.210	0.136	−0.302	0.319
Muscat Blanc à Petits Grains	0.275**	0.117	−0.029	0.138
Muscat Blanc à Petits Grains (R)	−0.143	0.123	−0.326***	0.125
Muscat of Alexandria	−0.163**	0.065	−0.640***	0.156
Nebbiolo	−0.172	0.116	−0.119	0.116
Nero d'Avola	−0.306	0.331	−0.265	0.421
Palomino Fino	0.426*	0.240	−0.060	0.143
Pedro Ximénez	−0.409***	0.126	−0.598***	0.139
Petit Verdot	0.131	0.130	0.102	0.154
Pinot Gris	0.101	0.092	0.003	0.068
Pinot Meunier	−0.285***	0.084	0.006	0.218
Pinot noir	−0.155***	0.043	−0.174***	0.061
Prosecco	−0.240*	0.133	−0.333**	0.165
Riesling	−0.346***	0.088	−0.205***	0.063
Roussanne	−0.315***	0.113	−0.573**	0.233
Ruby Cabernet	0.164	0.135	0.049	0.122
Sangiovese	−0.139	0.096	−0.088	0.098
Sauvignon blanc	−0.204***	0.045	−0.115	0.076
Savagnin Blanc	−0.017	0.198		
Sultaniye	0.844***	0.144	0.219	0.181
Sémillon	−0.187***	0.056	−0.022	0.061
Taminga	0.142	0.113		
Tarrango	−0.357	0.510	−0.262***	0.089
Tempranillo	0.123	0.119	0.168	0.136
Touriga Nacional	−0.535*	0.324	−0.561	0.362
Trebbiano Toscano	−0.344*	0.180	−0.661***	0.096
Tribidrag	−0.226	0.190	−0.156	0.208
Verdelho	−0.172**	0.070	−0.085	0.072
Vermentino	−0.394**	0.188	−1.374***	0.387
Viognier	0.001	0.084	0.139*	0.081
Adelaide Hills	0.064	0.058	0.175**	0.083
Adelaide Plains	−0.075	0.099	0.362***	0.094

Table 3: Continued.

Model →	(3)		(4)	
Dependent variable →	ln_CoV_yield		ln_CoV_revenue (ha)	
Independent variable ↓	Coeff	SE	Coeff	SE
Alpine Valleys	−0.092	0.085	0.054	0.084
Beechworth	−0.088	0.102	0.185	0.203
Bendigo	0.033	0.061	0.236***	0.077
Big Rivers-other	−0.067	0.118	0.120	0.091
Blackwood Valley	0.233***	0.088	0.350***	0.113
Canberra District	0.228***	0.080	0.162	0.114
Central Ranges-other	0.616***	0.097	0.466***	0.095
Central Victoria-other	0.204	0.274	0.434*	0.261
Clare Valley	−0.103	0.089	0.159***	0.060
Coonawarra	0.153*	0.082	0.362***	0.061
Cowra	0.287***	0.105	0.327***	0.101
Eden valley	−0.049	0.054	0.033	0.075
Fleurieu-other	0.415***	0.077	0.539***	0.108
Geelong	−0.025	0.081	−0.539***	0.122
Geographe	0.030	0.083	0.227***	0.074
Gippsland	0.215**	0.101	−0.355**	0.157
Glenrowan	−0.158*	0.087	−0.247	0.250
Goulburn Valley	−0.265***	0.100	0.157**	0.077
Grampians	−0.051	0.070	0.112	0.082
Granite Belt	0.454***	0.086	0.123	0.103
Great Southern	0.165**	0.071	0.215**	0.083
Greater Perth -other	−0.474	0.154		
Gundagai	−0.016	0.101	−0.051	0.102
Hastings River	0.006	0.139		
Heathcote	−0.282*	0.165	−0.197	0.174
Henty	−0.009	0.073	−0.289**	0.113
Hilltops	−0.032	0.084	0.073	0.076
Hunter Valley	0.455***	0.054	0.340***	0.082
Langhorne Creek	0.129*	0.066	0.517***	0.056
Limestone Coast-other	−0.024	0.050	0.234***	0.068
Macedon ranges	0.191**	0.083	0.046	0.115
Manjimup	0.263**	0.114	0.320**	0.157
Margaret River	−0.044	0.051	−0.011	0.088
McLaren Vale	0.144*	0.079	0.321***	0.052
Mornington Peninsula	0.098	0.078	−0.152	0.130
Mudgee	0.649***	0.055	0.424***	0.075
Murray Darling-Swan Hill (NSW)	−0.455***	0.091	−0.124	0.078
Murray Darling-Swan Hill (vic)	−0.436***	0.056	−0.135**	0.068
North East Victoria-other	0.010	0.088	0.186*	0.110
Northern Rivers-other	−0.414***	0.116	−0.157	0.160
Northern Slopes	0.399***	0.137	−0.114	0.106
Orange	0.093*	0.055	0.314***	0.079
Padthaway	−0.095**	0.047	0.227***	0.061
Peel	0.116	0.142	−0.373**	0.157
Pemberton	0.199	0.181	0.185	0.305
Perricoota	0.530***	0.101	0.436	0.278
Perth Hills	−0.067	0.263	−0.159*	0.091
Port Phillip-other	−0.009	0.135	−0.117	0.127
Pyrenees	0.325***	0.081	0.316***	0.101
Qld-other	0.373**	0.160	−0.057	0.105
Riverina	−0.667***	0.049	−0.194**	0.079
Riverland	−0.648***	0.051	0.222***	0.057
Rutherglen	0.042	0.090	0.293***	0.077
SA-other	0.026	0.125	0.274***	0.066
South Burnett	0.867***	0.082	0.218**	0.100
South Coast-other	−0.039	0.150	−0.337*	0.175
Southern Highlands	0.410*	0.222		
Southern New South Wales-other	0.024	0.135	−0.086	0.135

Table 3: Continued.

Model →	(3)		(4)	
Dependent variable →	ln_CoV_yield		ln_CoV_revenue (ha)	
Independent variable ↓	Coeff	SE	Coeff	SE
Strathbogie Ranges	0.062	0.145	0.114	0.315
Sunbury	0.191*	0.108	−0.101	0.336
Swan District	0.090	0.149	0.116	0.129
Tasmania	−0.300***	0.066	−0.503***	0.107
Tumbarumba	0.117*	0.071	−0.069	0.145
Upper Goulburn	0.404***	0.128	0.462***	0.119
WA-other	−0.312**	0.146	−0.057	0.131
Western Plains	0.656***	0.247	0.025	0.283
Western Victoria-other	0.167	0.133	0.257**	0.122
Wrattonbully	0.144	0.098	0.390***	0.093
Yarra Valley	−0.041	0.052	−0.080	0.090
ln_area	−0.110***	0.014	−0.027*	0.015
Constant	−0.117	0.121	−0.494***	0.129

The dependent variables of models (1) and (2) are the natural logarithm of the coefficient of variation of yield and the natural logarithm of the coefficient of variation of revenue per ha, respectively. “Coeff” stands for coefficient and “SE” for robust standard errors. Statistical significance levels: *** = 1%, ** = 5%, and * = 10%.

aimed to control for all time-invariant observable and unobservable characteristics of each region, including both GST and GSP.

Since models (3) and (4) controlled for these region-specific characteristics, they provided more reliable estimates of the variety dummy variables than models (1) and (2). These variety dummies, which were not reported in Table 2 to save space, are shown in Table 3. The base variety selected was Syrah and the base region was the Barossa Valley. Importantly, the coefficient and statistical significance of each variety dummy were computed with respect to the base variety, which was Syrah in both models. This variety was chosen as the base because it is the most-planted variety in Australia, accounting for 30% of the country’s bearing area. The database used in this study (i.e., Anderson and Puga [8]) uses Syrah instead of Shiraz as the prime name for this variety, even though Shiraz is its more common name in Australia. The choice of the prime names is explained in Note 3 of the Supplementary Information. Anderson and Puga [8] provide a list of all varieties’ prime names and their synonyms.

In addition to setting the base variety as Syrah, models (3) and (4) were reestimated with the base variety selected from among the next five most-planted varieties: Cabernet Sauvignon, Chardonnay, Merlot, Sauvignon Blanc, and Pinot Noir. The regression results were then used to estimate the expected percentage difference in the CoV of a variety when compared to the six most-planted varieties. Table 4 shows the estimates for the CoV of yield for the 27 most-planted varieties, and Table 5 provides the same information for the CoV of revenue per ha. Overall, these results suggested variable and often substantial differences across some varieties in their CoV.

Besides showing variety dummy variables, Table 3 reports the region dummies for models (3) and (4). The Barossa Valley was set as the base region for both models as it is a well-known wine region that is by far the largest by bearing area after the three main hot irrigated regions (i.e., Riverland, Riverina, and Murray Darling-Swan Hill). Therefore, the coefficient and statistical significance of each region dummy were computed with respect to the Barossa Valley. The estimates were used to compute the expected difference in the coefficients of variation of yield and revenue per ha of a region compared to the Barossa Valley. Table 6 shows these expected differences for the 27 largest regions.

4. Discussion

The results of models (1) and (2), shown in Table 2, provided insights into how regions with different climates might differ in terms of yield and revenue variability. Hotter regions tend to exhibit less yield variation, the same as drier regions. This is consistent with the results (discussed in Note 4 of the Supplementary Information) of the models similar to model (1) but in which the independent variables of interest are the natural logarithm of yield and the natural logarithm of real price. These models suggest that regions with higher yields and lower prices exhibit lower yield variation. The main inland hot and dry irrigated regions (i.e., Riverland, Riverina, and Murray Darling-Swan Hill) have higher yields and lower prices when compared to most other regions in Australia. There are a few possible explanations for these differences in yield variability. Hotter regions are less prone to frosts, which may frequently have negative impacts in the cooler regions of Australia [7]. Drier regions may also be less susceptible to the major grape diseases, which are exacerbated by higher precipitation [15].

That said, the main explanation for these differences in yield variability could be related to the production systems of the regions. Most regions that are hot and dry are irrigated regions, meaning that growers in these areas may often reach their targeted yields by irrigating either more or less. However, in drought years, even irrigated regions may have

Table 4: Expected difference (%) in the coefficient of variation of yield of a variety when compared to the six most-planted varieties.

Variety	Area (%)	S	CS	C	M	SB	PN
Cabernet franc	0.2	−6	−4	8	19	16	10
Cabernet sauvignon	18.4	−2		12	24	20	15
Canada muscat	0.2	−44	−43	−36	−30	−32	−35
Chardonnay	14.8	−13	−11		10	7	2
Chenin blanc	0.3	−12	−11	0	10	7	2
Colombard	1.0	−23	−22	−12	−3	−6	−10
Côt	0.4	−12	−10	1	11	8	3
Durif	0.6	−11	−9	2	12	9	4
Garnacha tinta	1.3	−15	−13	−2	8	5	0
Gewürztraminer	0.5	−15	−14	−3	7	4	−1
Merlot	5.6	−21	−19	−9		−3	−7
Monastrell	0.6	−1	1	13	24	21	15
Muscat blanc à petits grains	0.7	32	34	51	66	61	54
Muscat of alexandria	1.3	−15	−13	−3	7	4	−1
Petit verdot	0.8	14	16	30	44	40	33
Pinot gris	3.4	11	13	27	39	36	29
Pinot noir	4.2	−14	−13	−2	8	5	
Prosecco	0.2	−21	−20	−10	−1	−3	−8
Riesling	2.2	−29	−28	−19	−11	−13	−17
Ruby cabernet	0.5	18	20	35	48	45	38
Sangiovese	0.3	−13	−11	0	10	7	2
Sauvignon blanc	4.4	−18	−17	−7	3		−5
Sémillon	2.6	−17	−15	−5	4	2	−3
Syrah	30.1		2	14	26	23	17
Tempranillo	0.6	13	15	29	42	39	32
Verdelho	0.7	−16	−14	−4	6	3	−2
Viognier	0.5	0	2	15	26	23	17
Average of above		−9	−7	5	16	13	7
Average of all varieties		−4	−2	10	21	18	12

"Area (%)" refers to the percentage of winegrape area planted to a variety in Australia as of 2023. Only those varieties with an area share higher than 0.2% are shown in this table. Those varieties are compared to the six most-planted varieties in the last six columns. S = Syrah; CS = Cabernet Sauvignon; C = Chardonnay; M = Merlot; SB = Sauvignon Blanc; PN = Pinot Noir. Each number represents the percentage difference in the coefficient of variation of yield that is expected from a variety in the first column when compared to one of the varieties in the last six columns. For example, Chardonnay is expected to have a coefficient of variation of yield that is 13% lower than the one of Syrah or 10% higher than the one of Merlot. The colour represents the level of significance of the coefficient used for computing each number: significant at the 1% level, significant at the 5% level, and significant at the 10% level, and not statistically significant when not highlighted. All these computations are based on the results of model (3). "Average of above" is the unweighted average of the varieties in the first column; "average of all varieties" is the unweighted average of the varieties in the first column and all the others with an area lower than 2%.

lower yields, because grower allocations of water tend to decrease and water prices spike in those years. With climate change, droughts are projected to become more prevalent in the future [16], meaning that these hot and dry regions may have higher yield variability, primarily due to lower yields in drought years.

Perhaps surprisingly, the results did not indicate that regions with a certain climate type exhibited more or less variation in revenue. The GST and GSP coefficients in model (2) were not statistically significant. This observation was also in line with the coefficient of determination (R^2) of model (2) being less than half that of model (1). This may be

Table 5: Expected difference (%) in the coefficient of variation of revenue per ha of a variety when compared to the six most-planted varieties.

Variety	Area (%)	S	CS	C	M	SB	PN
Cabernet franc	0.2	1	−1	−19	7	13	20
Cabernet sauvignon	18.4	2	0	−18	8	14	21
Canada muscat	0.2	−8	−10	−26	−3	3	9
Chardonnay	14.8	24	22	0	31	39	48
Chenin blanc	0.3	−10	−12	−28	−5	1	7
Colombard	1.0	−15	−16	−31	−10	−5	1
Côt	0.4	−15	−17	−32	−10	−5	1
Durif	0.6	−26	−27	−40	−21	−17	−11
Garnacha tinta	1.3	−24	−25	−39	−19	−14	−9
Gewürztraminer	0.5	−8	−10	−26	−3	3	9
Merlot	5.6	−6	−7	−24	0	6	12
Monastrell	0.6	−16	−17	−32	−11	−6	0
Muscat blanc à petits grains	0.7	−3	−4	−22	3	9	16
Muscat of alexandria	1.3	−47	−48	−58	−44	−41	−37
Petit verdot	0.8	11	9	−11	17	24	32
Pinot gris	3.4	0	−1	−19	6	12	19
Pinot noir	4.2	−16	−17	−32	−11	−6	0
Prosecco	0.2	−28	−29	−42	−24	−20	−15
Riesling	2.2	−19	−20	−34	−14	−9	−3
Ruby cabernet	0.5	5	3	−15	11	18	25
Sangiovese	0.3	−8	−10	−26	−3	3	9
Sauvignon blanc	4.4	−11	−12	−28	−6	0	6
Sémillon	2.6	−2	−4	−21	4	10	16
Syrah	30.1	0	−2	−19	6	12	19
Tempranillo	0.6	18	16	−5	25	33	41
Verdelho	0.7	−8	−10	−26	−3	3	9
Viognier	0.5	15	13	−7	22	29	37
Average of above		−7	−9	−25	−2	4	10
Average of all varieties		−20	−21	−36	−15	−10	−4

"Area (%)" refers to the percentage of winegrape area planted to a variety in Australia as of 2023. Only those varieties with an area share higher than 0.2% are shown in this table. Those varieties are compared to the six most-planted varieties in the last six columns. S = Syrah; CS = Cabernet Sauvignon; C = Chardonnay; M = Merlot; SB = Sauvignon Blanc; PN = Pinot Noir. Each number represents the percentage difference in the coefficient of variation of revenue per ha that is expected from a variety in the first column when compared to one of the varieties in the last six columns. For example, Cabernet Sauvignon is expected to have a coefficient of variation of revenue per ha that is 18% lower than the one of Chardonnay or 21% higher than the one of Pinot Noir. The colour represents the level of significance of the coefficient used for computing each number: significant at the 1% level, significant at the 5% level, and significant at the 10% level, and not statistically significant when not highlighted. All these computations are based on the results of model (4). "Average of above" is the unweighted average of the varieties in the first column; "average of all varieties" is the unweighted average of the varieties in the first column and all the others with an area lower than 2%.

because, while hotter and drier regions may have lower yield variability, this lower variability may be offset by higher price variability. Indeed, a similar model to (1) and (2) but with the natural logarithm of real price as a dependent variable (instead of the natural logarithm of yield or revenue per ha) suggested that the hotter and drier regions do indeed exhibit more price variation (results discussed in Note 5 of the Supplementary Information).

Table 6: Expected differences (%) in the coefficients of variation of yield and revenue per ha of a region when compared to Barossa Valley.

Region	Area		CoV difference (%)	
	ha	%	Yield	Revenue (ha)
Mudgee	1909	1.3	91	53
Hunter valley	2622	1.8	58	41
Pyrenees	878	0.6	38	37
Cowra	930	0.6	33	39
Great southern	2415	1.7	18	24
Coonawarra	5641	3.9	17	44
Wrattonbully	2696	1.9	16	48
Mclaren vale	7189	5.0	15	38
Langhorne creek	5812	4.0	14	68
Mornington peninsula	901	0.6	10	-14
Orange	1061	0.7	10	37
Swan district	893	0.6	9	12
Adelaide hills	3587	2.5	7	19
Rutherglen	790	0.5	4	34
Geographe	788	0.5	3	25
Yarra valley	2478	1.7	-4	-8
Margaret river	5592	3.9	-4	-1
Eden valley	2267	1.6	-5	3
Padthaway	3742	2.6	-9	25
Clare valley	4952	3.4	-10	17
Goulburn valley	1211	0.8	-23	17
Heathcote	1686	1.2	-25	-18
Tasmania	2069	1.4	-26	-40
Murray darling -swan hill (Vic)	8722	6.0	-35	-13
Murray darling -swan hill (NSW)	6992	4.8	-37	-12
Riverland	20054	13.8	-48	25
Riverina	17108	11.8	-49	-18

"Area" refers to the winegrape area planted in a region in Australia as of 2023. Only those regions with an area share higher than 0.5% are shown in this table. Each number in the last two columns represents the percentage difference in the coefficient of variation of yield or revenue per ha that is expected in a region when compared to Barossa Valley. For example, Mudgee is expected to have a coefficient of variation of yield that is 91% higher than that of the Barossa Valley. The colour represents the level of significance of the coefficient used for computing each number, also compared to Barossa Valley: significant at the 1% level, significant at the 5% level, and significant at the 10% level are not statistically significant when not highlighted. All these computations are based on the results of models (3) and (4).

Winegrape varieties were also observed to differ in their yield variability over time. These differences across varieties were often both statistically and agronomically/economically significant when compared to the six most-planted varieties (Table 4). Varieties such as Cabernet Sauvignon, Muscat Blanc à Petits Grains, Petit Verdot, Pinot Gris, Ruby Cabernet, Syrah, Tempranillo, and Viognier tend to exhibit higher yield variability. On the other hand, varieties such as Canada Muscat, Colombard, Riesling, Sauvignon Blanc, Sémillon, and Verdelho were observed to have more variable yields over the years studied.

Overall, a clear pattern in yield variability based on the colour of the varieties was not observed, which was evidenced by further analysis that suggested that there was no statistically significant difference in yield variability between red and white varieties (results discussed in Note 6 of the

Supplementary Information). This finding differs from the previous observations reported by Fernandez-Mena et al. [17] which indicated that white winegrape varieties showed larger differences between actual and targeted yields than red varieties. However, the two studies are not directly comparable because the methods and explanatory variables in both studies differ and the study areas are not the same (Languedoc-Roussillon in France versus Australia).

Similar to the observations for yield variability, it was found that grape varieties frequently differed in their revenue variability. When observed, these statistically and economically significant differences in revenue variability were evident when comparing varieties (Table 5). Chardonnay, Tempranillo, and Viognier were observed to have more variable revenues over the years studied. Meanwhile, Colombard, Côt, Durif, Garnacha Tinta, Muscat of Alexandria, Pinot Noir, Prosecco, Riesling, and Verdelho exhibited lower revenue variation.

Despite some differences in the varieties which demonstrated the highest variability in either yield or revenue, it was found in general that the varieties that exhibited higher yield variation also exhibited greater revenue variation, and vice versa. Unlike with yields, there appeared to be overall differences in revenue variation based on the colour of the varieties. Further statistical analysis suggested that on average, white varieties exhibited 9.5% higher CoVs than red varieties, and that difference was statistically significant at the 5% level (results discussed in Note 7 of the Supplementary Information).

Regions also differed in their degree of yield and revenue variation, and the interregional differences observed were often large (Table 6). The regions with less yield variability were often hotter and drier, and included the main three hot irrigated regions (i.e., Riverland, Riverina, and Murray Darling-Swan Hill). However, there were some exceptions, notably Tasmania. Regions exhibited levels of revenue variability that were in line with their yield variability, although this was not always the case. The Riverland was the most extreme example of such a case, as this region has a low level of yield variability but a high level of revenue variability.

Based on the price dynamics of winegrapes, in years with higher yields, the price would be expected to be lower due to a higher supply of winegrapes, if demand remains constant [18]. Therefore, it might be expected that regions would have greater differences in yield than in revenue variability. However, the differences between yield and revenue variability were observed to have similar magnitudes across varieties (Tables 1, 4 and 5) and regions (Tables 1 and 6).

To address the main reasons which might have influenced yield variability in the time period under study, it must be noted that wine-producing countries such as Australia differ from Europe in that many geographical indications of European countries place limits on winegrape yields [19]. That said, in winegrowing countries such as Australia, growers may sometimes purposely reduce yields in order to achieve quality targets [20]. For example, 10% of Australia's grape growers perform crop thinning, and in some regions that proportion may be more than 50% [21]. However, most of Australia's grape production is not subject to crop thinning, and target yields are usually set at higher levels. Therefore, interannual variations in yield in Australia could mostly be explained by weather events, including droughts, and by management practices (see review by Clingeleffer [4]).

While there has been a substantial body of research related to yield variability, there are still some areas in which a lack of knowledge exists. An example of such an area relates to the degree to which alternate bearing affects winegrape production. Alternate bearing is a phenomenon in which a year with high yields is followed by a lower-yielding year, and vice versa. Since this phenomenon is induced by weather events, regional weather tends to synchronise alternate bearings in farms that are located within the same region, usually leading to biennial differences in yields [22]. Alternate bearing is very evident in perennial crops such as apple, olive, mango, citrus, pistachio, litchi, dates, and avocado [23]. Smith and Samach [24] argue that grapes do not exhibit a great degree of alternate bearing due to canopy management and other strategies. That said, the degree to which alternate bearing manifests in grapes is still unknown, and there is some evidence of this phenomenon for table grapes in some Australian regions (see Dahal et al. [25]). However, this phenomenon is less clear-cut in the case of winegrapes, and requires further investigation before it could be considered as a legitimate driver of yield variability.

Despite the usefulness of the methods in this study, there were some limitations that are worth noting. One relates to the cross-sectional nature of our statistical analyses. Trends in yields or revenues could lead to higher CoVs. These trends in yields were not quite evident from the data, but trends in prices could be more easily distinguished for certain variety-by-region combinations. Fortunately, using real revenues decreased this issue.

At the same time, it might also be expected that different results across periods might be due to the impact of changes in planting areas and/or even in the climates within regions. While it could be possible to divide the dataset into two separate periods to attempt to observe differences in the impact of variables such as GST and GSP across these periods, it was chosen not to do so due to the statistical advantages of working with a longer time series and larger sample sizes. That said, Note 8 of the Supplementary Information discusses estimates of models (1) to (4) with the data divided into two periods: 2001–2012 and 2013–2023. Research which aims to analyse interannual variation could use a panel data framework rather than a cross-sectional approach such as the one used in the current study. This is because panel data methods allow one to identify the impact of growing season weather and other drivers of seasonal yields (Blanc and Schlenker [26]).

Another potential issue is dealing with the (in practice incorrect) assumption that GSP and GST have the same effects across variety-by-region combinations. This might likely be also an issue when using panel data, as encountered by Puga et al. [7]. In the context of the current study, these differences could have been estimated using subsets of data for different regions. However, doing so would have decreased both the sample sizes and spectrum of GSTs and GSPs across regions, rendering models (1) and (2) less appropriate in their goal of determining the average influence of climatic variables on the CoVs of yield and revenue.

Another limitation may also relate to the use of the CoV as an index for measuring variability. Due to its mathematical formula, the CoV gives equal weight to positive and negative deviations from the average yield or revenue. Future research could use other indices or techniques that might allow for the decomposition of this variability into positive and negative shocks. That is, positive or negative effects on yield or revenue variation.

The CoV of revenue could also be decomposed by an alternative approach, that is, using yield and price variability. Note 9 of the Supplementary Information discusses estimations using the CoV of real price as the dependent variable. Yet, further research could look at more formal treatments of this type of decomposition, perhaps based on the work of Piggott [27], who introduced a method for decomposing revenue variation into components due to supply variability, demand variability, and an interaction between them. Subsequent research on variability decomposition might also be useful (e.g., Qiao et al. [28]).

5. Conclusion

Hotter and drier regions exhibit lower interannual yield variability. This may primarily be explained by growers in these regions having more options to irrigate their vines. However, in the wake of climate change, and with higher water prices in drier years, Australia's wine regions may expect higher yield variability in the future than was observed over the period of our study. Furthermore, despite having less variable yields, growers in hotter and drier regions experience similar levels of revenue variability to those in cooler and wetter regions, due to greater price variability.

It was also evident from the analysis that there are differences in yield and revenue variability across varieties. Possible explanations are related to management practices and the impact of weather events, including droughts. However, more research is needed to better understand and quantify the impact of the mechanisms influencing yield variability, including differences across varieties. A better understanding will also be important in the future, considering that revenues appeared to vary as much as yields, so this knowledge may help growers to stabilise both yields and revenues, for example, by guiding choices regarding new planting material.

Data Availability

The data used for this analysis are provided in the Supplementary Materials and freely available from the website of the University of Adelaide's Wine Economics Research Centre: (Puga et al. [8]) Database of Australian Winegrape Vine Area, Crush, Price and Per Hectare Volume, and Value of Production, by Region and Variety, 1956 to 2023, Wine Economics Research Centre, University of Adelaide https://economics.adelaide.edu.au/wine-economics/databases.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

The Supplementary Material of this paper includes a Stata do file and all the data that we have used for this article as both Stata data files and Excel files. Also, for those who do not use Stata, the Supplementary Material also includes a PDF with the code and results from that code. The notes mentioned in the manuscript are explained or discussed. As well as, we mention that the results, to which these notes referred to, can be found in the 442-page "Output" PDF. (*Supplementary Materials*)

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