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German Puga and Kym Anderson

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Contact details:
Wine Economics Research Centre
School of Economics
University of Adelaide
SA 5005 AUSTRALIA
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Winegrape yield and revenue variability in Australia

Germán Puga[1*] and Kym Anderson[1,2]

[1]Wine Economics Research Centre, School of Economics and Public Policy, The University of Adelaide, Adelaide, SA 5005, Australia
[2]Arndt-Cordon Department of Economics, Australian National University, Canberra, ACT 2601, Australia
[*]Corresponding author: german.puga@adelaide.edu.au

Abstract

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 is to determine whether there are differences in yield and revenue variability across climates, varieties, and regions in Australia. To do so, we estimate statistical models of the impact of those three variables on the coefficient of variation of yield and gross revenue per hectare. The results suggest that hotter and drier regions exhibit lower inter-annual yield variability, something that may be largely explained in the past by the use of irrigation but which may change in the future with climate change and higher water prices. The results also show that there are sometimes differences in yield and revenue variability not only across regions but also between varieties.

Keywords: grape yield, grape revenue, coefficient of variation, viticulture, climate change, alternate bearing

Introduction

Winegrowers appreciate low year-to-year variations in grape yields. Yield variations are sometimes caused by extreme events such as droughts (Zamorano et al., 2021) or high unexpected pest pressures (Puga et al., 2021). However, yield variability is mostly influenced by vine management and weather differences across seasons (Ellis et al., 2020). 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 (Clingeleffer, 2010). This knowledge is increasingly important because obtaining consistent yields is becoming more difficult with climate change (Merot et al., 2022).

The aim of this study is to determine whether there are differences in yield and revenue variability across climates, varieties, and regions in Australia. We compute coefficients of variation (CoV) for different variety-by-region combinations over the 2001-22 period. We then regress these CoV on different variables. In doing so, we provide insights into overall yield and revenue variability throughout those years. While we discuss some of the possible reasons explaining yield and revenue variability, this study does not intend to provide a causal link between the variables used in our models and yield or revenue variability. Nor does it seek to identify the variables influencing yield in a given season, for which process-based models (e.g., Leolini et al. (2022)) or panel data models (e.g., Puga et al. (2023)) may be more suitable.

Materials and methods

Data

We use a new dataset developed by Anderson and Puga (2023) that provides time series on area, production, and price by variety and region, as well as many other variables and indexes. We use these data to calculate CoV of yield (i.e., production per hectare) and gross revenue per hectare (revenue, hereafter).[1] The CoV is calculated as the ratio of the standard deviation to the mean. It is therefore a meaningful indicator for comparing the degree of variation between varieties, regions, or variety-by-region combinations even though the means are very different. For calculating the CoV, we use data from 2001 to 2022, after dropping the data for unidentified varieties. Table 1 shows the CoV for the regions and varieties with the largest shares of area.

[Location for Table 1]

We also use data on growing season average temperature (GST) and growing season precipitation (GST) from Anderson and Puga (2023). GST is one of the most-used climate indexes to represent temperature in viticulture (Liles and Verdon-Kidd, 2020, Puga et al., 2022a), and GSP is another commonly used index that has a high correlation with other precipitation-related variables (Puga et al., 2022b).

Statistical models

With the main objective of uncovering the extent to which yield variability differs across regions with different GST and GSP, we estimated:

$$ln\_CoV\_Yield_{v,r} = \alpha + \beta_1 GST_r + \beta_2 GSP_r + \varphi_v + \theta ln\_area_{v,r} + \varepsilon_{v,r}. \tag{1}$$

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 ($ln\_area_{v,r}$) serves as a control variable, and θ is its

[1] While variability in costs of production also are highly relevant, cost data by region and variety are unavailable to match the comprehensive yield and gross revenue data available.

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, we estimated:

$$ln\_CoV\_Revenue/ha_{v,r} = \alpha + \beta_1 GST_r + \beta_2 GSP_r + \varphi_v + \theta ln\_area_{v,r} + \varepsilon_{v,r}. \qquad (2)$$

The right-hand side of this model is the same as that in model (1). The difference 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), we estimated another model in which the dependent variable is again the natural logarithm of the coefficient of variation of yield:

$$ln\_CoV\_Yield_{v,r} = \alpha + \varphi_v + \gamma_r + \theta ln\_area_{v,r} + \varepsilon_{v,r}. \qquad (3)$$

The difference between this model and model (1) is that this model includes region dummy variables (γ_r) instead of GST and GSP. These region dummies aim to capture all time-invariant observable and unobservable characteristics of each region, including their climate. Therefore, by indirectly controlling for more region-specific characteristics, the coefficients of the variety dummies are more reliable than those of model (1). At the same time, the region dummies in this model also provide information on differences in yield variability across regions.

We also estimated a similar model to (3) but for analysing revenue variability, where the right-hand side is the same as in model (3) but the left-hand side (the dependent variable) is the same as in model (2):

$$ln\_CoV\_Revenue/ha_{v,r} = \alpha + \varphi_v + \gamma_r + \theta ln\_area_{v,r} + \varepsilon_{v,r}. \qquad (4)$$

There is a double justification for the use of the natural logarithm of CoV as opposed to CoV in models (1) to (4). Firstly, this specification leads to a more straightforward interpretation of the coefficients: it is easier to analyse proportional changes in the CoV than changes in the CoV themselves. Secondly, using the natural logarithm of the dependent variable can help mitigate issues of heteroskedasticity and deal with outlying or extreme values by narrowing the range of the variable (Wooldridge et al., 2020).

The CoV of both yield and revenue per ha is expected to be smaller for those variety-by-region combinations with larger areas. That is the reason behind the inclusion of $ln\_area_{v,r}$ as a control variable in models (1) to (4). Since this control variable and the dependent variable in each model are in natural logarithms, the θ coefficients are easy-to-interpret elasticities. These specifications seem accurate based on a visual analysis of the plots in Figure 1. These relationships are less smooth and evident when graphing each CoV against the area, as opposed to their natural logarithms.

[Location for Figure 1]

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, we assumed that $\varepsilon_{v,r} \sim (N, \sigma^2/\omega_{v,r})$, where the $\omega_{v,r}$ are analytic weights. We set the analytic weights to be the average area across the time period for each variety-by-region combination.

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

Results

Table 2 shows the estimation results of models (1) and (2). Model (1) fits the data quite well, explaining 60% of the variation in the natural logarithm of the CoV of yield. By contrast, model (2) explains only half as much (i.e., 30%) of the variation in its dependent variable compared with model (1). As expected, the coefficients of the natural logarithm of area in both models are negative and highly statistically significant, consistent with what is observed in Figure 1.

[Location for Table 2]

The coefficients of GST and GSP in model (1) are statistically significant at the 1% level. The interpretation of the GST coefficient is that a 1°C higher GST is associated with a 9.1% lower CoV of yield. (This is calculated as (EXP(coefficient)-1)*100.) The interpretation of the GSP coefficient is that a 10mm higher GSP is associated with a 1% increase in the CoV of yield. While the coefficients of GST and GSP in model (2) have the same signs as those in model (1), they are not statistically significant.

Table 3 shows the results of models (3) and (4). The coefficients and standard errors of the natural logarithm of area in both models are similar to those obtained in models (1) and (2), but the coefficients of determination (R^2) are higher than for models (1) and (2). Specifically, models (3) and (4) explain, respectively, 80% and 59% of the variation in the dependent variable. These higher coefficients of determination are expected because models (3) and (4) incorporate region dummy variables that aim to control for all time-invariant observable and unobservable characteristics of each region, including both GST and GSP.

[Location for Table 3]

Since models (3) and (4) control for all these region-specific characteristics, they provide more reliable estimates of the variety dummy variables than models (1) and (2). Those variety dummies, which are not reported in Table 2 to save space, are shown in Table 3. Importantly, the coefficient and statistical significance of each variety dummy are with respect to the base variety, which is Syrah in both models.

In addition to setting the base variety as Syrah, we re-estimated models (3) and (4) with the base variety being the next five most-planted varieties: Cabernet Sauvignon, Chardonnay, Merlot, Sauvignon Blanc, and Pinot Noir. We then used those regression results 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 suggest differences across some varieties in their CoV.

[Location for Tables 4 and 5]

Besides showing variety dummy variables, Table 3 reports the region dummies for models (3) and (4). Barossa Valley is set to be the base region for both models, so the coefficient and statistical significance of each region dummy are with respect to this region. We used those estimates to compute the expected difference in the coefficients of variation of yield and revenue per ha of a region compared to Barossa Valley. Table 6 shows these expected differences for the 28 largest regions.

[Location for Table 6]

Discussion

The estimation results of models (1) and (2), shown in Table 2, provide insights into how regions with different climates differ in terms of yield and revenue variability. Hotter regions seem to exhibit less yield variation, the same as drier regions. There are a few possible explanations for these differences in yield variability. Hotter regions are less prone to frosts, which often have negative impacts in the cooler regions of Australia (Puga et al., 2023). Drier regions may be less susceptible to the major grape diseases, which are enhanced by higher precipitation (Agosta et al., 2012).

That said, the main reason explaining these differences in yield variability may be related to the production systems of the regions. Most regions that are hot and dry are irrigated regions, meaning that growers in these regions can often reach their targeted yields by irrigating more or less. However, in drought years even the irrigated regions can have lower yields, because grower allocations of water tend to be shrunk and water prices spike in those years. With climate change, droughts are projected to become more prevalent in the future (Remenyi et al., 2020), meaning those regions may have higher yield variability due to lower yields in drought years.

The results do not suggest regions with a certain climate type exhibit more or less revenue variation. This is in line with the coefficient of determination (R^2) of model (2) being half of that in model (1). This may be because, while hotter and drier regions may have lower yield variability, that may offset by higher price variability. Indeed, a similar model to (1) and (2) but with the natural logarithm of price as a dependent variable suggests that the hotter and drier regions do indeed exhibit more price variation (results available from the authors).

Winegrape varieties also differ in how much their yields vary throughout time. These differences across varieties are often both statistically and agronomically/economically significant when compared to the six most-planted varieties (see Table 4). Varieties such as Fiano, Muscat Blanc à Petits Grains, Petit Verdot, Pinot Gris, Syrah and Tempranillo seem to exhibit higher yield variability. Others, such as Colombard, Gewürztraminer, Riesling, Sauvignon Blanc and Verdelho seem to have more variable yields across years. Overall, there does not seem to be a clear pattern based on the colour of the varieties, which is evidenced by further analysis that suggests there is no statistically significant difference between red and white varieties (results available from the authors). This finding might differ from research findings by Fernandez-Mena et al. (2023) that suggest white winegrape varieties show larger differences between actual and targeted yields (although that study is not directly comparable with the present one).

Likewise, varieties often differ in their revenue variability. These sometimes statistically and economically significant differences are evident when comparing varieties (see Table 5). Chardonnay, Tempranillo and Viognier seem to have more variable revenues across the years. Meanwhile, Colombard, Garnacha Tinta, Gewürztraminer, Merlot, Muscat of Alexandria, Pinot Noir, Riesling and Verdelho seem to exhibit higher revenue variation.

While these lists may seem a bit different to those for yield variability, the varieties that exhibit higher yield variation also exhibit higher revenue variation, and vice-versa. As is the case for yields, there does not seem to be a clear pattern based on the colour of the varieties, and further analysis suggests there is no statistically significant difference in revenue variation between red and white varieties (results available from the authors).

Regions also differ in their degree of yield and revenue variation, and their inter-regional differences are often large (see Table 6). The regions with less yield variability are often hotter and drier and include the main three hot irrigated regions (i.e., Riverland, Riverina, and Murray Darling-Swan Hill). However, there are some exceptions, notably Tasmania. Regions exhibit levels of revenue variability that are in line with their yield variability, although not always. Riverland is 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 lower due to a higher supply of winegrapes if demand remains constant (Puga et al., 2019). Therefore, we might expect regions to have higher differences in yield than revenue variability.

However, the differences between yield and revenue variability have similar magnitudes across varieties (see Table 1 and compare Table 4 with Table 5) and regions (see Table 1 and compare the second-last and last column of Table 6).

There is a caveat, however, when interpreting the results for the CoV of revenue. It is that trends, when present, lead to higher CoV. We tested whether there are significant trends that may lead to higher CoV. While trends do not seem to be present for yields, they are present in prices sometimes, hence influencing revenues. This means that part of some high CoV in revenues may be explained by trends, either due to price increases or decreases during the period.

What are the main reasons influencing yield variability? In many geographical indications of European countries, there are often limits on winegrape yields (Conca Messina et al., 2019). That is usually not the case in non-European countries like Australia, but growers sometimes get lower yields than what they could achieve due to quality reasons (Poni et al., 2018). For example, 10% of Australia’s grape growers perform crop thinning, and in some regions that proportion is more than 50% (Nordestgaard, 2019). However, most of Australia’s grape production is not subject to crop thinning, and target yields are usually set at higher levels. Therefore, inter-annual variations in yield in Australia are mostly explained by weather events, including droughts, and by management practices (see Clingeleffer (2010) for a review of variables influencing yield variability).

While there has been a substantial body of research related to yield variability, there are still some areas in which there is relatively little knowledge. 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 synchronize alternate bearing in farms that are located within the same region, leading to (usually) biennial differences in yields (Samach and Smith, 2013). Alternate bearing is very evident in perennial crops such as apple, olive, mango, citrus, pistachio, litchi, dates and avocado (Sharma et al., 2019). Smith and Samach (2013) 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: there is some evidence of this phenomenon in the case of table grapes in some Australian regions (see Dahal et al. (2019)), but it is less clear-cut in the case of winegrapes.

Conclusion

Hotter and drier regions exhibit lower inter-annual yield variability. Among other reasons, this may be explained by growers in these regions having more options to irrigate their vines. However, in the wake of climate change, and with high water prices in drier years, Australia’s wine regions may have higher yield variability in the future than in the period of our study.

Further, despite having less variable yields, growers in hotter and drier regions experience similar level of revenue variability to those in cooler and wetter regions, due to greater price variability.

It is also evident from our analysis that there are differences in yield and revenue variability across varieties. Possible explanations relate 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 is important considering that revenues seem to vary as much as yields, so this understanding may help growers stabilise both yields and revenues, for example, by helping them make better plant material choices when planting new vines.

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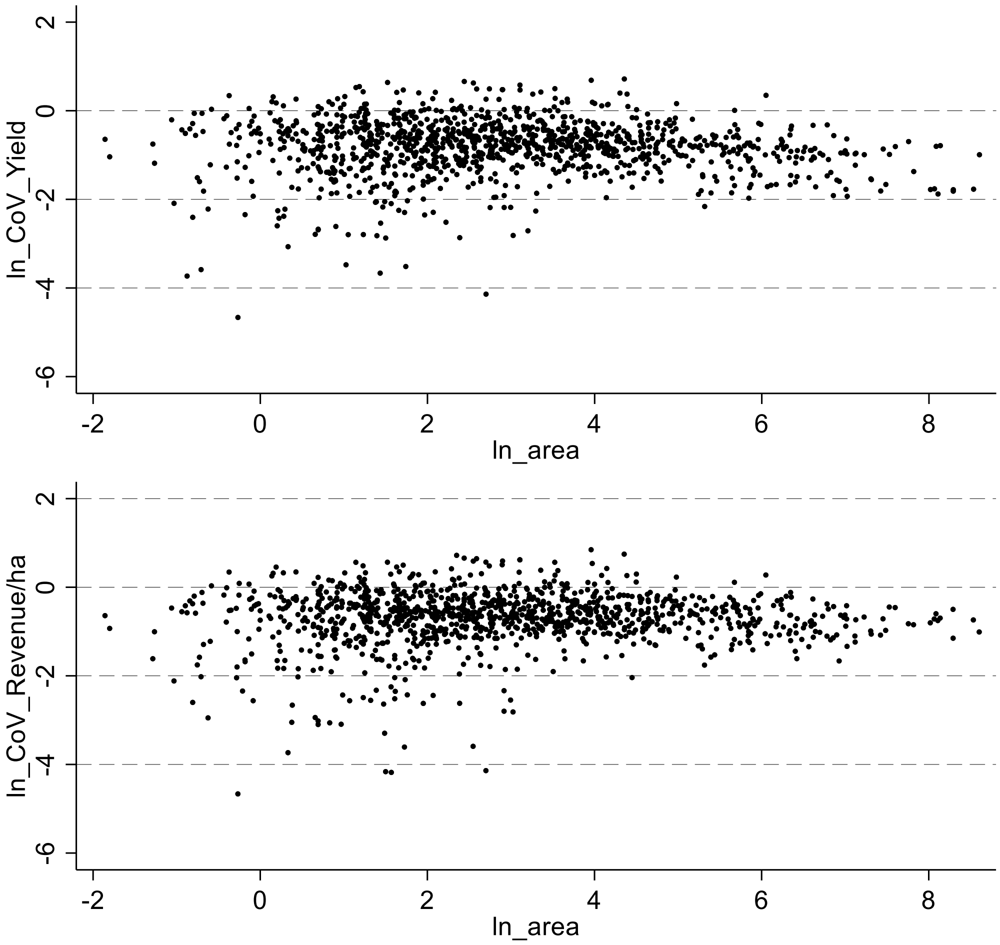

Figure 1: Scatterplots showing each observation as a function of the natural logarithm of its coefficient of variation and the natural logarithm of its area.

Table 1: Yield, revenue per ha, and coefficients of variation (CoV) for the regions and varieties with a bearing area higher than 2,000 ha in 2022.

	Area (ha)	Yield (t/ha)	Revenue/ha (AUD)	CoV yield	CoV revenue/ha
Region					
Riverland	19850	21.8	9154	0.61	0.79
Riverina	17108	14.9	5695	0.68	0.85
Barossa Valley	11445	6.2	7190	0.59	0.69
Murray Darling - Swan Hill (Vic)	8722	19.1	9138	1.69	1.93
McLaren Vale	7160	7.3	9944	1.26	1.37
Murray Darling - Swan Hill (NSW)	6992	21.5	9476	1.14	1.14
Langhorne Creek	5864	11.0	11500	1.44	1.84
Margaret River	5592	4.9	7023	0.85	0.56
Coonawarra	5479	7.6	7916	0.69	0.72
Clare Valley	4973	4.6	5495	0.51	0.57
Padthaway	3608	9.5	9820	0.62	0.71
Adelaide Hills	3607	6.5	9385	0.78	0.81
Limestone Coast - other	3273	8.3	7454	0.76	0.79
Hunter Valley	2622	4.2	4336	1.12	0.79
Wrattonbully	2617	11.3	11846	0.69	0.84
Yarra Valley	2478	5.0	7887	0.76	0.50
Great Southern	2415	3.9	5027	0.99	0.62
Eden Valley	2195	5.1	7007	0.60	0.66
Tasmania	2069	5.3	14198	0.78	0.49
Variety					
Syrah/Shiraz	43280	6.1	6992	0.97	0.71
Cabernet Sauvignon	26441	6.3	6696	1.44	1.24
Chardonnay	21512	7.2	7666	0.92	0.71
Merlot	8163	6.8	6978	1.06	0.78
Sauvignon Blanc	6462	8.8	9705	1.19	0.98
Pinot Noir	6029	7.0	8882	1.32	1.33
Pinot Gris	4892	11.5	15016	3.60	2.90
Sémillon	3800	9.4	7832	0.96	0.74
Riesling	3179	7.4	8017	2.13	2.23

Notes: Average yield and revenue per ha and coefficients of variation (CoV) based on data from 2001 to 2022.

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	-0.096***	0.017	-0.019	0.015
GSP	0.001***	0.000	0.000	0.000
Variety dummy variables	Yes		Yes	
Region dummy variables	No		No	
ln_area	-0.158***	0.020	-0.082***	0.018
Constant	1.779***	0.389	0.191	0.291
R^2	0.599		0.303	

Notes: 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%.

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	-0.577***	0.137	-1.192***	0.180
Arneis	-1.127***	0.181	-0.657***	0.130
Barbera	-0.340	0.227	-0.274	0.179
Cabernet Franc	-0.190	0.137	-0.064	0.119
Cabernet Sauvignon	-0.058	0.049	0.016	0.032
Cayetana Blanca	0.052	0.266	-0.185	0.214
Chardonnay	-0.126**	0.048	0.172***	0.046
Chenin Blanc	-0.166	0.185	-0.189	0.197
Colombard	-0.264**	0.109	-0.292**	0.133
Crouchen	0.304**	0.146	-0.083	0.111
Côt	-0.233**	0.115	-0.145	0.122
Dolcetto	-1.997***	0.722	-2.254***	0.657
Durif	-0.055	0.188	-0.196	0.152
Fiano	0.533*	0.313	0.303	0.361
Garnacha Tinta	-0.166*	0.086	-0.275***	0.101
Gewürztraminer	-0.222**	0.097	-0.277***	0.076
Graciano	-1.085***	0.360	-0.727	0.572
Grüner Veltliner	-0.547***	0.134	-0.524***	0.098
Lagrein	-0.550***	0.165	-0.488***	0.120
Marsanne	-0.211	0.281	-0.187	0.165
Merlot	-0.280***	0.088	-0.125**	0.061
Monastrell	-0.020	0.295	-0.165	0.230
Montepulciano	-0.506*	0.266	-0.655**	0.266
Muscadelle	0.105	0.154	-0.140	0.181
Muscat Blanc à Petits Grains	0.372***	0.120	-0.062	0.141
Muscat Blanc à Petits Grains (R)	-0.187	0.197	-0.413***	0.095
Muscat of Alexandria	-0.181	0.117	-0.714***	0.148
Nebbiolo	-0.254	0.183	-0.174	0.152
Nero d'Avola	-0.100	0.938	-0.639	0.951
Palomino Fino	0.426	0.328	-0.148	0.163
Pedro Ximénez	-0.402**	0.176	-0.666**	0.285
Petit Verdot	0.107	0.191	0.057	0.170
Pinot Gris	0.143**	0.068	0.031	0.060
Pinot Meunier	-0.375*	0.203	-0.107	0.212
Pinot Noir	-0.176**	0.068	-0.160**	0.064
Prosecco	-0.119	0.175	0.082	0.076
Riesling	-0.354***	0.110	-0.283***	0.057
Roussanne	-0.577*	0.319	-0.648**	0.309
Ruby Cabernet	0.157	0.212	0.090	0.119
Sangiovese	-0.122	0.114	-0.063	0.108
Sauvignon Blanc	-0.202***	0.058	-0.111	0.081
Sultaniye	0.960***	0.197	0.357	0.262
Sémillon	-0.178***	0.052	-0.058	0.053

Tarrango	-0.299	0.291	-0.318**	0.132
Tempranillo	0.151	0.165	0.124	0.126
Touriga Nacional	-0.899**	0.344	-0.821	0.578
Trebbiano Toscano	-0.626***	0.193	-0.804***	0.116
Tribidrag	-0.078	0.252	-0.210	0.265
Verdelho	-0.250**	0.103	-0.166*	0.086
Vermentino	-0.326	0.249	-0.643***	0.239
Viognier	-0.105	0.137	0.056	0.102
Adelaide Hills	0.014	0.030	0.072*	0.039
Adelaide Plains	-0.103	0.092	0.216***	0.074
Alpine Valleys	-0.169**	0.078	0.024	0.075
Beechworth	0.117	0.126	0.253**	0.114
Bendigo	-0.059	0.074	0.130*	0.065
Big Rivers - other	0.159**	0.075	0.219***	0.068
Blackwood Valley	0.159*	0.087	0.248***	0.080
Canberra District	0.055	0.096	0.161*	0.088
Central Ranges - other	0.625***	0.099	0.526***	0.089
Central Victoria - other	0.441***	0.099	0.482***	0.084
Clare Valley	-0.098***	0.023	0.103***	0.027
Coonawarra	0.128***	0.015	0.265***	0.020
Cowra	0.192***	0.050	0.333***	0.050
Eden Valley	-0.066	0.046	-0.062	0.048
Fleurieu - other	0.317***	0.054	0.524***	0.051
Geelong	-0.341***	0.080	-0.472***	0.075
Geographe	0.015	0.073	0.096	0.069
Gippsland	-0.248**	0.104	-0.317***	0.096
Glenrowan	-0.710***	0.101	-0.509***	0.090
Goulburn Valley	-0.518***	0.064	-0.064	0.056
Grampians	0.013	0.076	0.036	0.065
Granite Belt	-0.028	0.115	0.005	0.095
Great Southern	0.114***	0.041	0.094**	0.044
Gundagai	-0.066	0.077	-0.039	0.068
Heathcote	-0.350***	0.058	-0.287***	0.046
Henty	-0.190*	0.101	-0.219**	0.097
Hilltops	0.061	0.075	0.037	0.070
Hunter Valley	0.394***	0.029	0.304***	0.035
Langhorne Creek	0.084***	0.013	0.419***	0.019
Limestone Coast - other	-0.056*	0.028	0.123***	0.032
Macedon Ranges	0.072	0.108	0.042	0.098
Manjimup	0.354***	0.122	0.302***	0.107
Margaret River	-0.059***	0.019	-0.123***	0.031
McLaren Vale	0.097***	0.012	0.174***	0.011
Mornington Peninsula	0.047	0.061	-0.157**	0.064
Mudgee	0.417***	0.039	0.427***	0.043
Murray Darling-Swan Hill (NSW)	-0.357***	0.022	-0.196***	0.038
Murray Darling-Swan Hill (Vic)	-0.565***	0.039	-0.093*	0.052
North East Victoria - other	-0.035	0.063	0.117*	0.065
Northern Rivers - other	-0.649***	0.177	-0.240	0.153

Northern Slopes	-0.200 *	0.113	-0.145	0.102
Orange	0.039	0.059	0.241 ***	0.056
Padthaway	-0.109 ***	0.027	0.133 ***	0.033
Peel	-0.600 ***	0.147	-0.416 ***	0.125
Pemberton	0.376 ***	0.067	0.252 ***	0.068
Perricoota	0.535 ***	0.086	0.526 ***	0.078
Perth Hills	-0.300 ***	0.109	-0.202 **	0.092
Port Phillip - other	-0.287 ***	0.097	-0.157 *	0.088
Pyrenees	0.186 **	0.073	0.236 ***	0.063
Qld - other	-0.322 **	0.143	-0.136	0.117
Riverina	-0.744 ***	0.010	-0.178 ***	0.015
Riverland	-0.670 ***	0.024	0.159 ***	0.017
Rutherglen	0.040	0.091	0.216 ***	0.069
SA - other	0.049	0.058	0.207 ***	0.048
South Burnett	0.091	0.115	0.237 **	0.095
South Coast - other	-0.630 ***	0.130	-0.385 ***	0.116
Southern New South Wales - other	-0.258 **	0.123	-0.050	0.103
Strathbogie Ranges	0.064	0.079	0.222 ***	0.076
Sunbury	-0.642 ***	0.120	-0.210 **	0.099
Swan District	0.037	0.073	0.084	0.073
Tasmania	-0.370 ***	0.043	-0.509 ***	0.052
Tumbarumba	0.083	0.086	-0.097	0.080
Upper Goulburn	0.444 ***	0.097	0.399 ***	0.090
WA - other	-0.742 ***	0.097	-0.112	0.087
Western Plains	0.456 ***	0.106	0.096	0.084
Western Victoria - other	0.133	0.132	0.244 **	0.117
Wrattonbully	0.142 ***	0.028	0.296 ***	0.036
Yarra Valley	-0.061 *	0.035	-0.175 ***	0.042
ln_area	-0.103 ***	0.029	-0.066 ***	0.023
Constant	-0.145	0.238	-0.367 *	0.185
R^2	0.801		0.588	

Notes: 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%.

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	-17	-12	-6	9	1	-1
Cabernet Sauvignon	18.3	-6		7	25	16	13
Chardonnay	14.9	-12	-7		17	8	5
Chenin Blanc	0.3	-15	-10	-4	12	4	1
Colombard	1.0	-23	-19	-13	2	-6	-8
Côt	0.5	-21	-16	-10	5	-3	-6
Durif	0.6	-5	0	7	25	16	13
Fiano	0.3	70	80	93	125	109	103
Garnacha Tinta	1.2	-15	-10	-4	12	4	1
Gewürztraminer	0.5	-20	-15	-9	6	-2	-4
Merlot	5.6	-24	-20	-14		-7	-10
Monastrell	0.6	-2	4	11	30	20	17
Muscat Blanc à Petits Grains	0.7	45	54	65	92	78	73
Muscat of Alexandria	1.3	-17	-12	-5	10	2	0
Petit Verdot	0.8	11	18	26	47	36	33
Pinot Gris	3.4	15	22	31	53	41	38
Pinot Noir	4.2	-16	-11	-5	11	3	
Prosecco	0.2	-11	-6	1	17	9	6
Riesling	2.2	-30	-26	-20	-7	-14	-16
Ruby Cabernet	0.5	17	24	33	55	43	40
Sangiovese	0.3	-11	-6	0	17	8	6
Sauvignon Blanc	4.5	-18	-13	-7	8		-3
Syrah	29.9		6	13	32	22	19
Sémillon	2.6	-16	-11	-5	11	2	0
Tempranillo	0.6	16	23	32	54	42	39
Verdelho	0.7	-22	-18	-12	3	-5	-7
Viognier	0.5	-10	-5	2	19	10	7
Average of above		-5	1	8	27	17	14
Average of all varieties		-12	-7	0	16	8	5

Notes: 'Area (%)' refers to the percentage winegrape area planted to a variety in Australia as of 2022. 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. Variety abbreviations: S = Syrah, CS = Cabernet Sauvignon, C = Chardonnay, M = Merlot, SB = Sauvignon Blanc, and 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, Cabernet Sauvignon is expected to have a coefficient of variation of yield that is 6% lower than the one of Syrah or 7% higher than the one of Chardonnay. 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**, **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%.

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	-6	-8	-21	6	5	10
Cabernet Sauvignon	18.3	2		-14	15	14	19
Chardonnay	14.9	19	17		35	33	39
Chenin Blanc	0.3	-17	-19	-30	-6	-8	-3
Colombard	1.0	-25	-27	-37	-15	-17	-12
Côt	0.5	-14	-15	-27	-2	-3	2
Durif	0.6	-18	-19	-31	-7	-8	-3
Fiano	0.3	35	33	14	53	51	59
Garnacha Tinta	1.2	-24	-25	-36	-14	-15	-11
Gewürztraminer	0.5	-24	-25	-36	-14	-15	-11
Merlot	5.6	-12	-13	-26		-1	4
Monastrell	0.6	-15	-17	-29	-4	-5	0
Muscat Blanc à Petits Grains	0.7	-6	-8	-21	6	5	10
Muscat of Alexandria	1.3	-51	-52	-59	-45	-45	-43
Petit Verdot	0.8	6	4	-11	20	18	24
Pinot Gris	3.4	3	1	-13	17	15	21
Pinot Noir	4.2	-15	-16	-28	-4	-5	
Prosecco	0.2	9	7	-9	23	21	27
Riesling	2.2	-25	-26	-37	-15	-16	-12
Ruby Cabernet	0.5	9	8	-8	24	22	28
Sangiovese	0.3	-6	-8	-21	6	5	10
Sauvignon Blanc	4.5	-11	-12	-25	1		5
Syrah	29.9		-2	-16	13	12	17
Sémillon	2.6	-6	-7	-21	7	5	11
Tempranillo	0.6	13	11	-5	28	27	33
Verdelho	0.7	-15	-17	-29	-4	-5	-1
Viognier	0.5	6	4	-11	20	18	24
Average of above		-7	-9	-23	6	4	10
Average of all varieties		-20	-21	-33	-9	-10	-6

Notes: 'Area (%)' refers to the percentage winegrape area planted to a variety in Australia as of 2022. 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. Variety abbreviations: S = Syrah, CS = Cabernet Sauvignon, C = Chardonnay, M = Merlot, SB = Sauvignon Blanc, and 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 14% lower than the one of Chardonnay or 15% 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**, **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%.

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	52	53
Hunter Valley	2622	1.8	48	35
Cowra	930	0.6	21	39
Pyrenees	878	0.6	20	27
Wrattonbully	2617	1.8	15	34
Coonawarra	5479	3.8	14	30
Great Southern	2415	1.7	12	10
McLaren Vale	7160	5.0	10	19
Langhorne Creek	5864	4.1	9	52
Mornington Peninsula	901	0.6	5	-15
Rutherglen	790	0.5	4	24
Orange	1061	0.7	4	27
Swan District	893	0.6	4	9
Geographe	788	0.5	2	10
Adelaide Hills	3607	2.5	1	7
Barossa Valley	11445	7.9		
Margaret River	5592	3.9	-6	-12
Yarra Valley	2478	1.7	-6	-16
Eden Valley	2195	1.5	-6	-6
Clare Valley	4973	3.4	-9	11
Padthaway	3608	2.5	-10	14
Heathcote	1686	1.2	-30	-25
Murray Darling-Swan Hill (NSW)	7028	4.9	-30	-18
Tasmania	2069	1.4	-31	-40
Goulburn Valley	1211	0.8	-40	-6
Murray Darling-Swan Hill (Vic)	8699	6.0	-43	-9
Riverland	19850	13.7	-49	17
Riverina	17108	11.8	-52	-16

Notes: 'Area' refers to the winegrape area planted in a region in Australia as of 2022. 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, Mudge is expected to have a coefficient of variation of yield that is 52% higher than that of 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**, **significant at the 10% level**, and not statistically significant (when not highlighted). All these computations are based on the results of models (3) and (4).