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What explains changes in grape varietal mixes in Australia's wine regions?

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Abstract

In an ever-more-competitive global beverage market, vignerons compete for the attention of consumers by trying to differentiate their wine from others while also responding to technological advances, climate change, and evolving demand patterns. In doing so, they highlight their regional and varietal distinctiveness while keeping an eye on changes in consumer preferences for different varieties. This paper examines and seeks to explain the extent to which winegrape varietal mixes vary across regions and over time within Australia and relative to the rest of the world. It reports changes in indexes of similarity across regions, and indexes of concentration in the winegrape varietal mix within regions. Nationally the varietal mix has become less differentiated and closer to that of France and the world as a whole. However, individual regions within Australia are becoming more concentrated in their mix of varieties and more differentiated from other Australian regions. We estimate supply response models based on a Nerlovian adaptive profit expectations and partial acreage adjustment framework. These models do not provide insights into many of the variables influencing vignerons' planting decisions, but they help explain recent changes in varietal mixes. The results suggest changes in varietal mixes are more motivated by expected revenues than by what may work best based on the climate of each region. In the wake of climate change and global wine demand premiumizing, some Australian vignerons may find their region is too warm for producing high-quality wine with the winegrape varieties planted there.

Keywords: grape cultivar, winegrape concentration, winegrape similarities, supply response, acreage response, Nerlovian adaptive expectations and partial adjustment model, climate change

JEL classification: D24, L66, Q13

1. Introduction

Australia's vignerons have both produced and exported around 180 winegrape varieties from 70+ regions and sub-regions over the past two decades. However, as in the rest of the world (see Anderson and Nelgen (2021), Puga and Anderson (2023)), the main French varieties have become more dominant, and regions' varietal mixes have become more concentrated. This happened while the nation's total bearing area changed dramatically in delayed responses to a rise and then a fall in winegrape prices: during 2000-08 the area expanded by two-thirds (having already doubled in the 1990s), and then it shrunk by one-sixth by 2014 before plateauing (Figure 1).

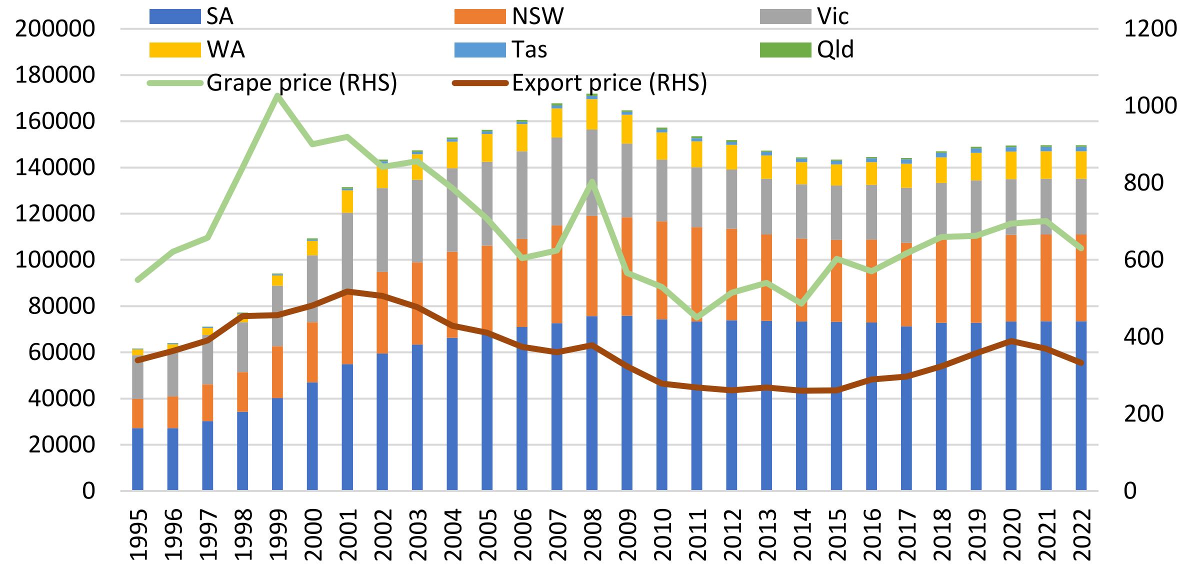

Figure 1: Winegrape bearing area by state (bars, left axis in hectares), and prices of winegrapes and of exported wine (lines, right axis in AUD/tonne and cents/litre), Australia, 1995 to 2022.

Source: Anderson and Puga (2023a).

Deciding which varieties of winegrapes to plant is difficult, for two key reasons. First, it depends on how well each variety is expected to grow and at what cost in the vigneron's particular location/terroir, and how that expectation is evolving as the perception of the location's climate changes. Adaptation strategies include switching to warmer-climate or more-resilient grape varieties for that region and sourcing more grapes of their favoured varieties from cooler regions with a higher latitude or elevation or closer to the sea.

The second key reason the grower's varietal choice is difficult is that it depends on the expected revenue per hectare of each variety relative to near substitutes, and that varies through time with fluctuations in relative yields per hectare and in global availability and changes in consumer preferences and hence in relative grape prices. For varieties that are coming into favour, there is on the one hand a shared incentive to shift towards them. On the other hand, there is a possible benefit from differentiating one's offering from the mainstream and having a wider-than-average mix of varieties. That may be especially so for smaller vignerons heavily reliant on direct-to-consumer wine sales through the cellar door and an associated loyalty club.

Globalization is complicating the issue for vignerons because greater market openness increases the opportunity to specialize in production and sell more abroad – but it also increases potential import competition and so may reduce their domestic sales. This two-edged sword has emerged rapidly: the extent to which global wine production is exported (and global wine consumption is met by imports) has increased from around 20% in the 1990s to 30% in the 2000s, 40% in the 2010s and now almost 45% (Anderson and Pinilla, 2021). By choosing to specialize and become more export-focused, a vigneron is taking on more risk in terms of not just overall variation in yield per hectare and domestic prices but also foreign prices, foreign exchange rates, and market access risks.

The remainder of this article is organised as follows. Section 2 describes a newly compiled annual Australian database for 72 wine-growing regions and 23 vintages (2001 to 2023). The data are more precise for South Australian regions (comprising half of the nation's vine bearing area) than for the rest of the country's regions. Section 3 provides, as background, a summary of the evolution and current state of the varietal mixes in those regions. This summary is based on an index of varietal concentration and an index of varietal similarity, as well as on some relatively simple statistical analyses that rely on these indexes. They reveal the considerable but varying extent to which both concentration and similarity have altered over the past two decades. Section 4 describes the Nerlovian adaptive expectations and partial adjustment framework, in which we base the supply response models that are detailed in Section 5. Then Section 6 presents and discusses the results of these supply response models for South Australia. Last, Section 7 concludes by drawing out implications for the nation's industry.

2. Data

Fortunately, South Australia, which accounts for almost half the national vineyard area, is well served with data because of the required annual reporting by South Australian growers to Vinehealth Australia (2014 and earlier) and now published by Wine Australia (2022a and earlier). For the rest of Australia, there has been no official data on the bearing or total area of winegrapes by variety and region since 2015. That was when the Australian Bureau of Statistics (ABS) stopped collecting data on national, state and regional vine areas by variety. Nor did it collect them in 2009, 2011, 2013 and 2014 (see ABS (2015 and earlier)). So until recently it had not been possible to trace changes for those missing years in that basic statistic outside of South Australia. That led Anderson and Puga (2023a) to compile a database for wine regions outside South Australia and thus also for each of the other States and the nation as a whole. They did so by bringing together available annual data from various sources for winegrape crush volumes and prices by variety and region (Wine Australia (2022b and earlier)), and then making a series of assumptions (detailed in the Appendix in Anderson and Puga (2023b)) to estimate the missing bearing area data.

In total, there are 72 regions in the database, a little more than the 65 legally defined Geographic Indications (GIs) because of changes in definitions of GIs over time including the emergence of some sub-regions, and despite needing to aggregate some small new regions. Area, production, and price data are available for 118 'prime' varieties (prime as defined by Anderson and Nelgen (2020) based on Robinson et al. (2012) or otherwise www.vivc.de). There are also another 64 more minor prime varieties whose data are aggregated into 'other red' or 'other white' for confidentiality reasons. Of that total of 183 varieties, wines from 178 of them have been exported at some time in the past two decades – but just five accounted for around four-fifths of the total volume of Australia's wine exports in the past five years.

3. Background

The varietal mix of the national vine area has cycled over the decades. Thanks to changes in domestic preferences, red varieties rose in importance in the 1960s and 1970s before being taken over by whites in the 1980s – and then regaining their dominance in the 1990s and holding on to it since then (Anderson, 2015). This mirrors changes since 1990 in the rest of the world, where red's share rose from 46% to 49% by 2000 and to 56% by 2016 (Anderson and Nelgen, 2021). If China's obsession with reds is an important part of the reason for this century's colour swing, one might expect red's global share to fall over the 2020s given that, according to Anderson (2023), China's wine production has shrunk hugely and its imports have halved since 2017 – and almost completely stopped from Australia which is why the share of reds in Australia's wine exports has dipped recently.

The main varieties grown in Australia drifted away from the varieties commonly used up to the 1950s for fortified wines and toward the key varieties that produce premium still and sparkling wines (Figure 2). The country of origin of most of today's varieties is France. Again that change in Australia mirrors what is happening in the rest of the world, with key French varieties becoming more popular everywhere (Anderson and Nelgen, 2021). The extent of the swing toward French varieties in Australia leading up to the turn of the century was extreme. In the 1950s/early 1960s, the share originating from Spain was more than 40% while the French share was no more than that of Greece at just under 20%, with Turkey next at around 10% (because of Sultana). By the early 1980s, the shares of Spanish and French varieties had reversed, and by the turn of the century Spanish shares were less than 4% (because of Grenache's share falling from 20% in the late 1950s to 1% today) and France's had risen to almost 80% – and to 90% by 2011.

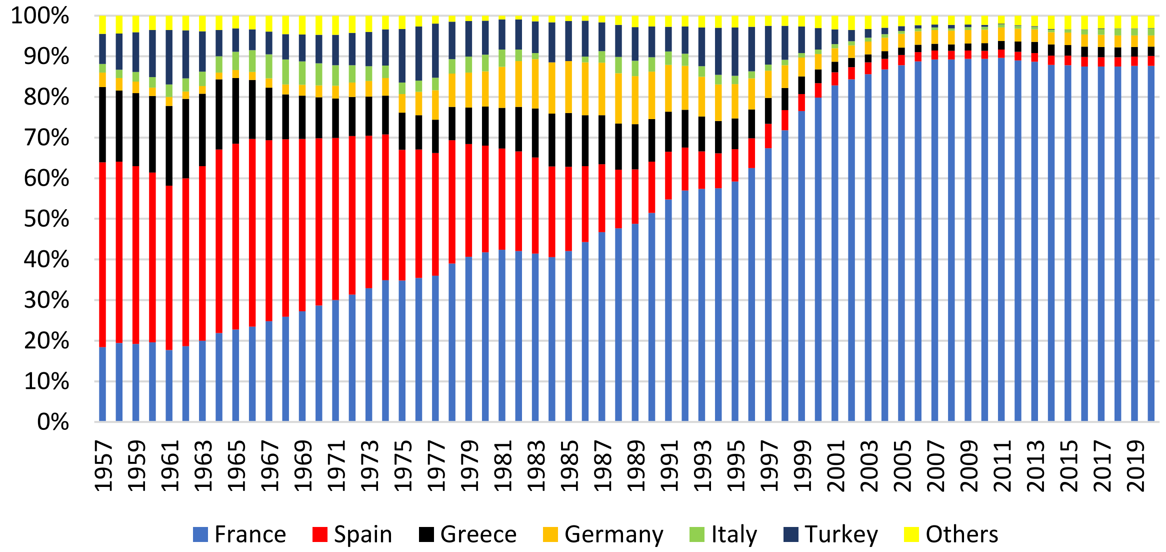

Figure 2: Evolution of the Australian varietal mix (in terms of bearing area) based on the country of origin of the winegrape varieties.
Source: Anderson and Puga (2023a).

Associated with the increasing similarity of Australia's national winegrape varietal mix with the world is a greater concentration on fewer varieties (Puga and Anderson, 2023). In Australia's case, the top ten varieties by area have accounted recently for 87% of the national area, whereas the share of the top ten in 2001 was 83%. True, many vignerons are exploring 'alternative' or 'emerging' varieties (see, e.g., Higgs (2019), Allen (2023)), but as yet those make up just 3.0% of the nation's vineyard area and 1.5% of its volume of exports.

For quantifying varietal concentration, we use the varietal concentration index (VCI) defined by Puga and Anderson (2023) as:

$$VCI_i = 100\left(\sum_{v=1}^{V} f_{i,v}^2\right). \tag{1}$$

Here, $f_{i,v}^2$ is the square value of the bearing area of variety v in region (or country) i as a proportion of the total winegrape bearing area in that region (or country). The same formula has been used for indexes in other disciplines. Two key examples are the Herfindahl–Hirschman concentration index in economics and the Simpson index in ecology (Simpson, 1949). The interpretation of the VCI is that if two different winegrape blocks are randomly chosen, the probability (expressed as a percentage) of those winegrape blocks having the same variety is equal to the value of the index.

In aggregate, the Australian VCI has increased from 12.0 in 2000 to 15.6 in 2016, well above the 2016 values for France, Italy and Spain – all of whose VCIs fell over that period (Anderson and Puga, 2023). The changes in Australia's regional VCIs between 2001 and 2022 are shown in Table A.1. Evidently, the varietal mixes of the warm irrigated regions have become a little less concentrated over those two decades, while the mixes of most other regions have become more concentrated, including three of the next largest (Barossa Valley, McLaren Vale and Coonawarra).

Besides looking at varietal concentration, we explore similarities in the varietal mix using the varietal similarity index (VSI), first introduced by Anderson (2010). The VSI for regions i and j takes the form:

$$VSI_{ij} = \frac{\sum_{v=1}^{V} f_{i,v} f_{j,v}}{\left(\sum_{v=1}^{V} f_{i,v}^2\right)^{1/2} \left(\sum_{v=1}^{V} f_{j,v}^2\right)^{1/2}}, \tag{2}$$

where $f_{i,v}$ ($f_{j,v}$) is the bearing area of variety v in region i (j) as a proportion of the total winegrape bearing area in that region. The VSI ranges between 0 and 1. The closer the index is to 1, the more similar the varietal mix between the two regions. More specifically, an index of 0 indicates a completely different mix of winegrape varieties, while an index of 1 means that both regions have exactly the same varieties and the same proportional area for each of those varieties.

This same formula can be used to compute the VSI between a region and Australia, or between a region (or Australia) and the world as a whole. Australia's convergence towards the global mix is evident as in 2001 the VSI for Australia vis-à-vis the world mix was 0.47, but in 2022 it was 0.66. The varietal mixes of all but two (small) wine regions of Australia have moved towards the global mix, and there are only eight regions whose VSIs vis-à-vis the world has moved by less than one-fifth: Adelaide Hills, Barossa Valley, and McLaren Vale in South Australia; Grampians, Mornington Peninsula, and Yarra Valley in Victoria; Western Australia's Swan District; and Tasmania (Table A.1).

The changes in the regional and state VSIs vis-à-vis the national varietal mix are quite varied. Tasmania's and Western Australia's VSIs have fallen a lot while Victoria's has risen from 0.85 to 0.96 and so is now almost the same as South Australia's and New South Wales'. The VSIs of the warm irrigated regions (along the Murray, Murrumbidgee, and Goulbourn rivers, plus Langhorne Creek and Padthaway) also have risen and moved into the 0.93 to 0.96 range. By contrast, for four of the cooler regions, their VSI relative to Australia's has fallen by between one-fifth and one-third since 2001 (Adelaide Hills, Mornington Peninsula, Tasmania, and Yarra Valley).

We use the method developed by Puga and Anderson (2023) to cluster some of the largest regions based on their varietal similarities. Figure 3 shows these clusters. The longer the horizontal lines linking regions or groups of regions, the more dissimilar they are. The regions represented in this figure are some major regions for which Nordestgaard (2019) provides data on their production systems. Using those data, Puga et al. (2022a) classify these regions into six groups. Figure 3 shows that regions with similar production systems are often more similar in their mix of winegrape varieties.

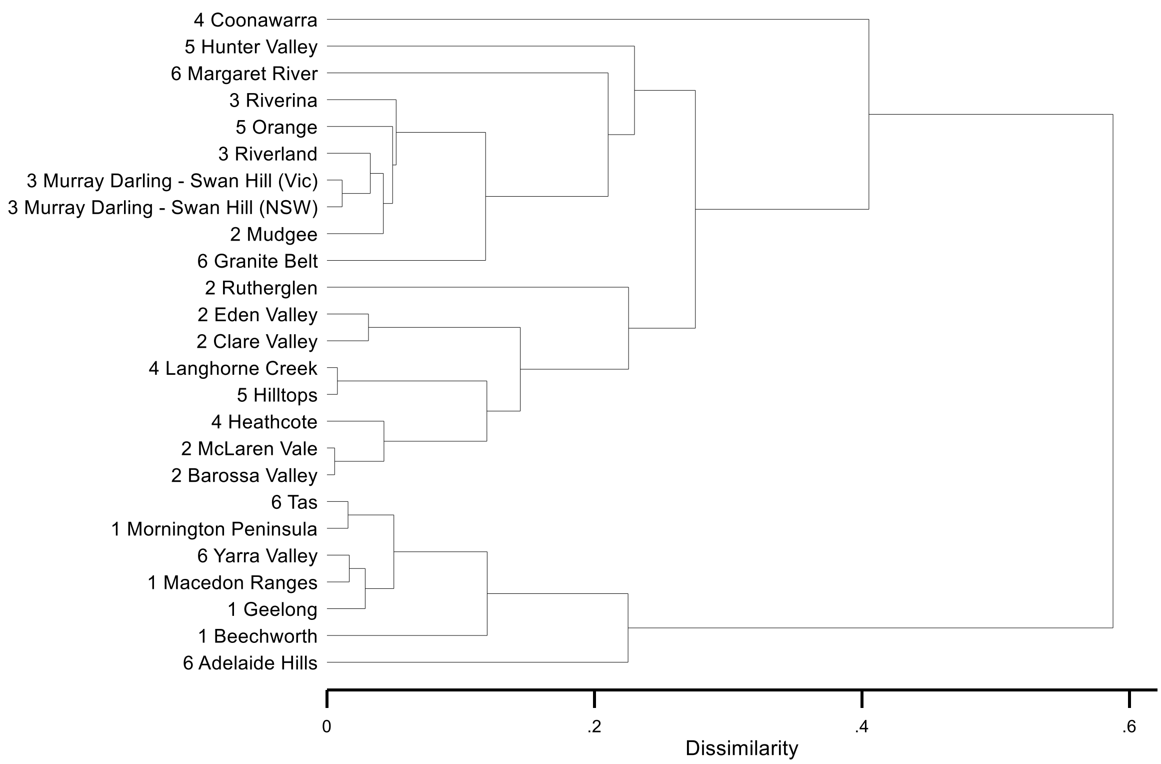

Figure 3: Dendogram based on 2023 VSIs.

Notes: VSI is the varietal similarity index. Dissimilarity = 1 - VSI. Longer horizontal lines linking regions or groups of regions are associated with lower similarities in their varietal mix. The numbers before the name of each region denote groups of regions with similar production systems, based on a classification by Puga and Anderson (2022) using data on 103 characteristics of the production system of each region (from Nordestgaard (2019)).

Source: Authors' compilation.

We may expect regions to have a more-similar varietal mix the more similar are their climates. Figure 4 shows the ideal growing season temperature ranges for some key varieties widely planted in Australia, according to Jones et al. (2011). Some varieties are better suited to some regions, and the climate of those regions often determines a big part of that suitability. Figure 3 suggests that some of the regions with a more similar varietal mix have more-similar climates. Indeed, the production systems of the regions depend to a certain extent on their climates.

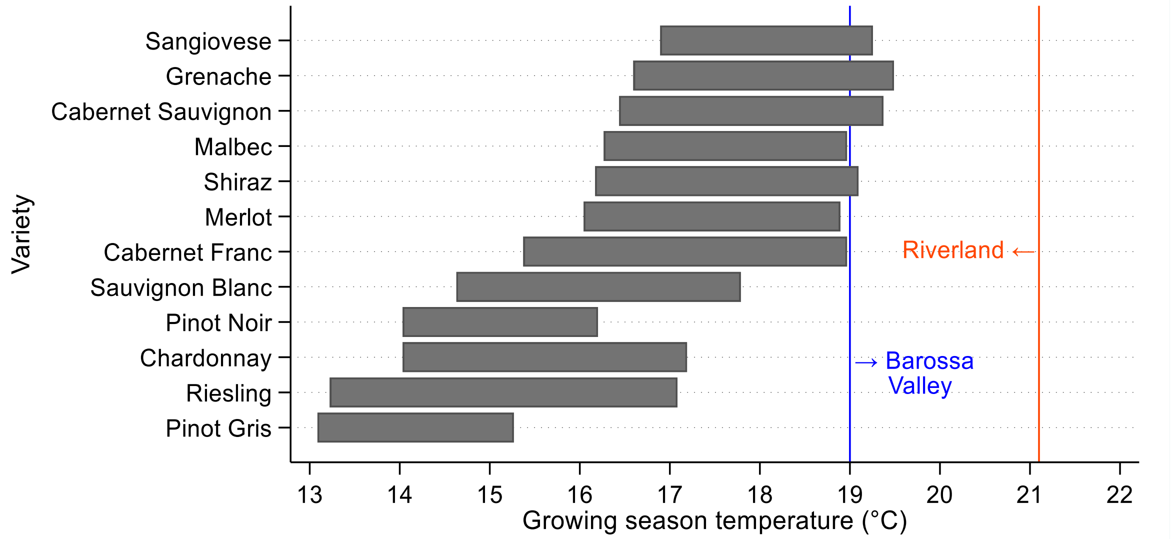

Figure 4: Ideal growing season temperature ranges for producing high-quality wine of different varieties.

Notes: Each horizontal bar represents the ideal growing season temperature range for producing high-quality wine according to Jones et al. (2011). Barossa Valley is the largest region after the hot irrigated regions, of which the Riverland is the largest.
Source: Adapted from Jones et al. (2011) by the authors.

We may also expect regions to become more similar when they share a more similar climate. For testing this, we first use data for 2002 and 2022 to calculate the difference in the bearing area of each variety in each region. We then use those area differences to calculate an index similar to the one given by equation (1). However, by using area differences between two years as opposed to total area, we obtain an index that takes values between -1 and 1. An index of -1 (1) would mean that the proportional area planted to each variety has changed in the opposite (the same) way between the two regions. The vertical axis of Figure 5 shows this index, while its horizontal axis shows the difference in growing season temperature between regions. However, Figure 5 does not show a negative relationship between this index and the difference in growing season temperature between the two regions. Indeed, when regressing this temperature difference on this index, the slope coefficient is not statistically significant.

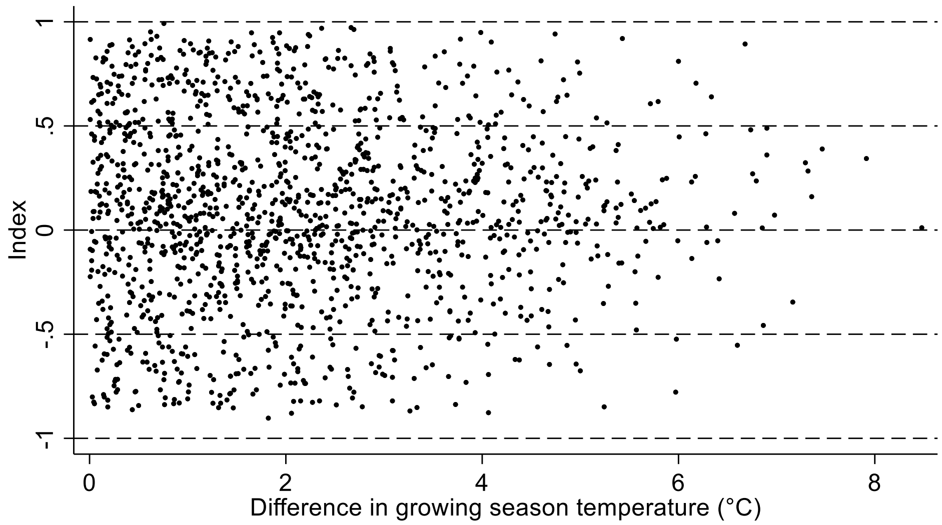

Figure 5: Index of change in varietal similarities across regions between 2002 and 2022 vs difference in their growing season temperature.

Source: Authors' compilation.

In the light of this considerable variation across regions in changes in their VSIs and VCIs over the past two decades, we turn now to see to what extent the changes in the varietal mix can be explained by changes in winegrape prices and gross revenues per hectare. It is clear from our data that there is considerable variation in prices and gross revenue per hectare across varieties and regions, and over time.

4. Theoretical framework

The two major frameworks in the supply response literature are the Nerlovian partial adjustment model and the supply function approach (Haile et al., 2015). Since the supply function approach demands more input data than we have available, we derive our models from the framework developed by Nerlove (1956a, 1956b). This framework has been used to analyse the dynamics of crop supply in a wide variety of settings (Vitale et al., 2009).

In Nerlove's model, the desired area ($Area_t^d$) in year t is given by:

$$Area_t^d = \alpha_1 + \alpha_2 Price_t^e + \upsilon_t. \tag{3}$$

In this equation, $Price_t^e$ is the expected price of the crop in year t; the α_s are parameters, with α_2 representing the long-run coefficient of supply response; and υ_t accounts for unobserved random variables affecting the area and has an expected value of zero.

Producers are assumed to move towards a long-run equilibrium or desired area planted to a given crop. However, full adjustment to the desired area is not feasible in the short run. The actual adjustment is expected to be just a fraction of the desired adjustment δ so that:

$$Area_t - Area_{t-1} = \delta\left(Area_t^d - Area_{t-1}\right) + \nu_t. \tag{4}$$

The δ is the partial adjustment coefficient and is expected to take a value between 0 and 1, hence the name of this coefficient. Like υ_t in equation (3), ν_t is also a random term with an expected value of zero.

The main reason why growers may not be in an equilibrium position at any point in time is because of adjustment costs (Nerlove, 1972). The inertia of production decisions also justifies the dynamic nature of the model (Hausman, 2011). The adaptive expectations parameter captures the non-static nature of area changes by taking values between zero and one. This assumption of partial adjustment has been criticized due to agronomic incentives such as crop rotation. Hendricks et al. (2014) provide theoretical and empirical evidence that the supply of annual crops may respond more to price shocks in the short run than in the long run. However, in the context of perennial crops, where there is no rotation, we expect the adaptive expectations parameter to be bounded between zero and one.

Since future prices for a crop are unknown, the expected prices should be based on a series of assumptions based on farmers' beliefs. The model also assumes that there is an expected price formed in each period. While this expected price changes year by year, price expectations are static, meaning that the expected price is predicted to be the same in all subsequent periods. The adaptive expectation hypothesis of Nerlove (1956a, 1956b) states that producers revise their price expectations based on their errors in the previous year. This hypothesis is an alternative to older expectation models such as the naïve expectation hypothesis (Ezekiel, 1938) in which the expected prices are the prices observed in the previous season.

Adaptive expectations imply that producers adjust their price expectations as a fraction γ of the mistake they made in the previous year[1]. In other words, the difference between the actual and the expected price in the previous year ($Price_t^e - Price_{t-1}^e$), so that:

$$Price_t^e - Price_{t-1}^e = \gamma(Price_{t-1} - Price_{t-1}^e) + \varepsilon_t. \tag{5}$$

The γ is the adaptive expectations coefficient and it is expected to take a value between 0 and 1. Again, ε_t is a random term with an expected value of zero.

Equation (5) can be solved so that:

$$Price_t^e = \gamma \sum_{i=1}^{\infty} (1-\gamma)^{i-1} Price_{t-i}. \tag{6}$$

The interpretation of this equation is that the expected price is a weighted sum of all past prices with a geometrically declining set of weights.

Equations (3), (4), and (5) can be combined so that:

$$Area_t = \beta_0 + \beta_1 Price_{t-1} + \beta_2 Area_{t-1} + \beta_3 Area_{t-2} + \epsilon_t. \tag{7}$$

The β_s are parameters to be estimated and ϵ_t is a zero-mean error term. The β_1 coefficient gives the short-run coefficient of price response. Further, even though the desired areas and the expected prices are not observed, it is possible to retrieve the long-run price response coefficient. It is α_2 from equation (3), which can be calculated as $-\beta_1/(\beta_2 + \beta_3 - 1)$. Since

[1] A theoretical limitation of the adaptive expectation hypothesis is that it is not derived from production theory (de Castro and Teixeira, 2012). Other price expectation hypotheses have been commonly used in Nerlovian partial adjustment models. The rational expectation hypothesis (Muth, 1961) assumes expectations are consistent with the underlying market structure and that producers use all the available information. Following Gardner (1976), future prices have been widely used to proxy expected prices. However, future prices are rarely available for crops such as winegrapes. Nerlove and Bessler (2001) review six models of expectation formation (including adaptive, rational, quasi-rational, and future prices) and recommend the quasi-rational model for estimating expected prices in agricultural supply analysis. The quasi-rational expectation hypothesis is potentially more realistic and easier to apply than the rational expectation hypothesis (Holt and McKenzie, 2003). Still, the literature is inconclusive and different types of price expectation models are commonly used. Adaptive expectations is a good alternative for cases with limited data, as in the present case.

both δ and γ should be bounded between zero and one, the long-run supply response should be larger than the short-run supply response.

An important consideration is that model (7) assumes that there is a separation of growers' expectations from their plans and decisions. While this separation assumption is theoretically incorrect, it is necessary for empirically analysing the problem of dynamic optimization behaviour under uncertainty (Nerlove and Bessler, 2001).

Ultimately, growers will make their investment decisions to increase their future expected profits. Under the Marshallian/Jorgensonian decision rule, a grower will plant a vineyard when:

$$MPK \geq MPK^{*} = \rho, \tag{8}$$

where MPK is the expected marginal product of capital during a vineyard's expected life cycle, MPK^{*} is the threshold in which it is optimal to plant, and ρ is the discount rate.

Dixit and Pindyck (1994) argue that the threshold in which it is optimal to invest is higher than the discount rate ρ because there is value in waiting and postponing the decision of investing. While the Marshallian/Jorgensonian decision rule considers uncertainty, the model of Dixit and Pindyck (1994) also assumes that investments have some unrecoverable investment costs and that a grower can invest in a project in the future if not doing it at present (Chirinko, 1996). The value of postponing an investment decision while trying to gather more information may also explain the nature of partial adjustments in the Nerlove (1956a, 1956b) model.

5. Supply response models

Perennial cropping involves long-term investments with long gestation intervals between planting and first harvesting (about three years in the case of winegrapes). Then after a period of intense productivity, perennial crops' productivity starts declining until the aged plants are removed. The Nerlovian partial adjustment framework has long been used for studying the supply of perennial crops. However, this framework has often been extended to account for differences between perennial and annual crop production.

One of the most widely used extensions of the Nerlovian framework to perennial crops consists of estimating plantings and removals equations separately. French and Matthews (1971) build on early studies to develop a theoretical framework to model the supply responses of perennial crops. In their model, area is estimated based on an identity function in which the total area equals the previous area, plus new plantings, minus removals. Recent examples of studies that distinguish between new plantings and removals (or net plantings) when modelling perennial crop supply are Devadoss and Luckstead (2010) and Ouattara et al. (2019).

Unfortunately, at present we do not have reliable data on new plantings and removals that would allow us to estimate these extensions of the Nerlovian framework. Therefore, we focus on total area data for South Australia. In other states, the data are available for bearing area as opposed to total area (Anderson and Puga (2023a), so using data for those states would be inappropriate for estimating these kinds of supply response models.

We first estimate a restricted Nerlovian supply response model, similar to the one specified in equation (7). However, our model is adapted to the specific case of changes in area by variety and region, and includes fixed effects. This Nerlovian adaptive profit expectations and partial acreage adjustment model is given by:

$$lnArea_{vr,t} = \beta_0 + \beta_1 lnPrice_{vr,t-1} + \beta_2 lnArea_{vr,t-1} + \beta_3 lnArea_{vr,t-2} + \varphi_{vr} + \tau_t + \epsilon_{vr,t}. \quad (9)$$

The dependent variable is the area of variety v in region r and year t. The independent variables are the price of that variety in that region in the previous year, the first and second lag of the dependent variable, group (variety-by-region) fixed effects (φ_{vr}), and time fixed effects (τ_t). The β_s are coefficients to be estimated, β_0 is a constant, and $\epsilon_{vr,t}$ denotes the error term.

The main difference between models (7) and (9) is that the latter includes fixed effects. The variety-by-region fixed effects capture time-invariant characteristics of each variety-by-region that influence its area, while the time fixed effects account for shocks that impact the changes in the area planted to winegrapes in a given year for all varieties and in all regions.

As with any Nerlovian supply response model, of particular interest are the coefficients of supply response. The β_1 coefficient is the short-run price response. The long-run price response is given by $-\beta_1/(\beta_2 + \beta_3 - 1)$. Since these variables are natural logarithms, these responses are elasticities.

As a robustness check, we estimate three modified versions of model (9). First, instead of using $lnPrice_{vr,t-1}$ as an independent variable, we use the lag of the price of variety v in region r relative to the average price of all varieties sold in that region and year. We also estimate two models in which we use an explanatory variable that depends on the revenue rather than the price. In the first of those models, that independent variable is the lag of the natural logarithm of the gross revenue per hectare of variety v in region r. This variable is intended to capture revenue expectations, hence we calculate it as a product between the price in a given year and the average yield across the time period. In the second of those models, the explanatory variable is the lag of the revenue of variety v in region r relative to the average revenue for all varieties sold in that region and year.

Besides estimating model (9), we estimate another perhaps even more ad-hoc model, following Alston et al. (2015). Unlike with model (9), here we estimate one model per region. This model is given by:

$$lnf_{v,t} = \beta_0 + \beta_1 lnCA_{v,t} + \beta_2 lnf_{vr,t-1} + \varphi_v + \tau_t + \epsilon_{v,t}. \quad (10)$$

The dependent variable is the natural logarithm of the share of total winegrape area planted to variety v in year t. The independent variables are the natural logarithm of a measure of comparative advantage for that variety in that year ($lnCA_{v,t}$), the lag of the dependent variable, variety fixed effects (φ_{vr}), and time fixed effects (τ_t). The β_s are coefficients to be estimated, β_0 is a constant, and $\epsilon_{vr,t}$ denotes the error term.

The measure of regional comparative advantage is given by:

$$CA_{v,t} = \frac{P_{v,t}Y_{v,t}}{\bar{P}_t\bar{Y}_t}. \quad (11)$$

For a variety v, this measure is the average revenue per hectare of that variety relative to the average revenue per hectare of all varieties in the region. However, in model (10) we use the 5-year moving average of the measure specified in equation (11). We calculate this moving average with the years for which there are available data, as sometimes there is no data available for some of the previous five years (e.g., in the early years).

Model (10) is also a Nerlovian partial adjustment model as it assumes that the interannual proportional change in varietal share is equal to a fixed fraction of the proportional difference between the desired share and the actual share in the previous year. Therefore, the

β_1 coefficient is the short-run supply elasticity, while the long-run supply elasticity is given by $\beta_1/(1-\beta_2)$.

We estimate models (9) and (10) using ordinary least squares (OLS). We estimate model (9) with robust standard errors clustered at the variety-by-region level to correct for heterogeneity given the differences between areas between variety-by-region combinations. Similarly, following Alston et al. (2015), we cluster the standard errors of model (10) due to the large differences between varietal shares.

6. Results and discussion

Table 1 shows the estimation results of model (9). The high coefficient of determination shows that this model fits the data very well, something we expect from a model with two lags of the dependent variable and so rich in fixed effects. The coefficients of the natural logarithm of the lags of price and area are positive as they are expected to be, and except for the coefficient of the second lag of the dependent variable, they are also statistically significant at the 1% level.

Table 1: Estimation results of model (9).

Variable	Coefficient	Standard error
$lnPrice_{vr,t-1}$	0.0744***	0.0186
$lnArea_{vr,t-1}$	0.7741***	0.0467
$lnArea_{vr,t-2}$	0.0027	0.0372
Constant	0.0067**	0.1565
Time fixed effects	Yes	
Variety-by-region fixed effects	Yes	
R^2	0.9939	

Notes: *** denotes statistical significance at the 1% level. Robust standard errors clustered at the variety-by-region level.

Of particular interest are the price elasticities. The short-run supply elasticity is 0.0744, while the long-run elasticity is 0.3334. Compared to previous supply response studies for annual crops, this short-run elasticity is smaller, but the long-run elasticity is in a similar range to those that are usually obtained for annual crops. The difference between the short-run supply response for annual crops and the present one for a perennial crop may be due to the fact that grape growing is a very capital-intensive activity with long investment horizons.

The fixed effects are omitted in Table 1 to save space, but Figure 6 shows a plot of the time fixed effects. These time fixed effects capture time shocks common to all variety-by-region combinations, so they account for overall changes in the area that are not explained by changes in prices. Figure 6 suggests that until 2008 vignerons might have been overly optimistic towards planting vineyards than what might be expected from the adaptive expectations hypothesis. The opposite case seems to have happened since 2008, although the observed negative trend may also be capturing the effects of inflation.

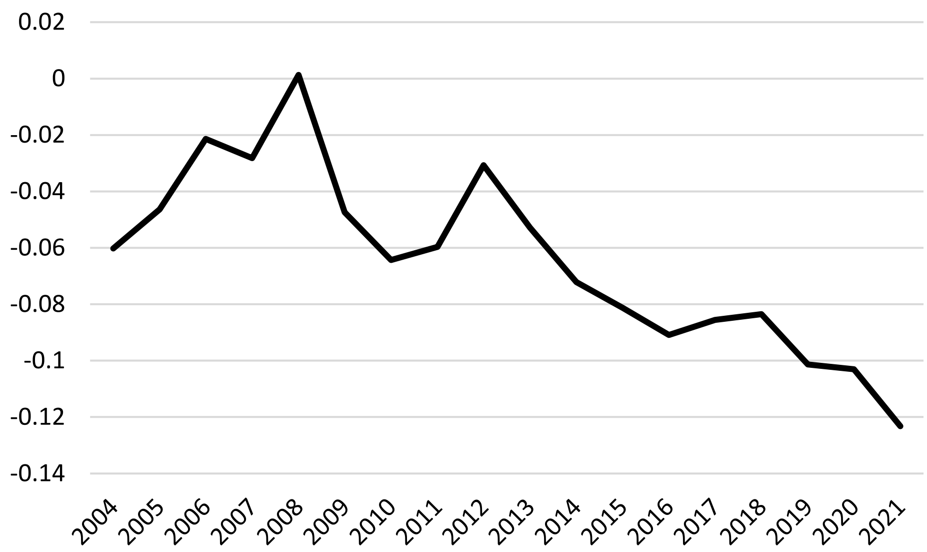

Figure 6: Line plot of time fixed effects from model (9).

We also used the results from model (9) to predict the area by variety and region in each year. Then, we regress the differences between the actual and predicted area values on variables such as region, variety, varietal colour, and varietal country of origin. In doing so, we intend to see whether the model under- or over-predicts the area based on any of these variables, which could point out other variables influencing growers' planting decisions. However, we do not find statistically significant results suggesting these under -or over-predictions, so the results are not presented here.

Besides looking at the results of model (9), it is also important to discuss some of the underlying assumptions. Since this is a restricted Nerlovian supply response model, the area by variety and region is projected to partially adjust based on the prices that growers expect for the grapes of that variety in that region. These expected prices are based on the adaptive expectations hypothesis. The rich fixed effects structure of model (9) allows us to account for many unobservable variables that may affect the area planted to a variety in a region.

Still, there are caveats to model (9). One of them is that it assumes that the changes in the area are a function of changes in prices, even though the decisions made by growers are likely to be more related to expected profits than to expected prices. Assuming that the expected yields are constant for each variety-by-region combination (while differing among them) means that the results would be the same if controlling for revenues in model (9), as opposed to simply controlling for prices. Indeed, using the lag of the gross revenue per hectare of variety v in region r ($lnRevenue_{vr,t-1}$) instead of $lnPrice_{vr,t-1}$ leads to almost identical results (Table A.2).

However, the same does not apply to costs. Even if assuming that the relative differences in the season's costs of producing each variety in each region are constant through time, overall changes in costs would lead to different profits. In other words, different results may be expected when controlling for profits instead of revenues despite the above-mentioned assumptions.

Further, on top of the differences in production costs between varieties and regions in each season, there are differences in the investment costs across varieties and regions, based on dissimilarities in plant material and production systems. These differences in investment costs are not considered in a Nerlovian adaptive profit expectations and partial acreage adjustment framework. An example of differences in investment costs arises when a grower replants an existing vineyard with a new variety as opposed to planting a new vineyard from scratch. Our data does not specify which of these two is the case in hand. However, this distinction may not be important considering the model assumes that there is a representative grower for each variety in each region.

The assumption of the representative grower has been criticized because the differences between the representative producer and the individual producers within a region can sometimes mislead the conclusions derived from regional-level data (Chen and Önal, 2012). Models with aggregated data can be limited by the unobserved heterogeneity caused by differences between farms within the same region (Koutchadé et al., 2018). This intra-regional variability can also be affected by differences in risk aversion between producers, information asymmetries, or credit market imperfections (Yu et al., 2017). Li et al. (2018) claim that regional-level data provide a good approximation of farm-level data if regions are small units of production and there is heterogeneity between regions. While recognizing the limitations of the assumption of the representative grower, we argue that these two conditions hold for most winegrape regions in our analysis.

Table A.3 reports the results of a variation of model (9) in which one of the explanatory variables is the lag of the price of variety v in region r relative to the average price of all varieties sold in that region and year. Compared to model (9), the short-run supply elasticity is a bit higher (0.0888 vs 0.0744), as is the long-run elasticity (0.3971 vs 0.3334). Table A.4 shows the results of another variation of model (9), in which the variation of the explanatory variables is the lag of the gross revenue per hectare of variety v in region r relative to the average revenue per hectare of all varieties sold in that region and year. These results are very similar to those reported in Table A.3, with the short-run supply elasticity being 0.0864 and the long-run elasticity being 0.3861.

Table 2 shows the estimation results of model (10) for each of the major regions in South Australia. As with model (9), the high coefficients of determination show that this model fits the data very well, something we also expect due to the inclusion of a lag of the dependent variable and variety fixed effects. The coefficients of the natural logarithm of the lag of the dependent variable are all positive and statistically significant at the 1% level. However, only three coefficients of the measure of competitive advantage are statistically significant. That said, and as expected, more of these coefficients become significant when not computing robust standard errors clustered at the variety level.

Table 2: Estimation results of model (10).

Region	$lnf_{v,t-1}$		$lnCA_{v,t}$			Obs.	R^2
	Coeff.	SE	Coeff.	SE	LR coeff.		
Adelaide Hills	0.8789***	0.0271	0.0317	0.0439	0.2621	229	0.9974
Adelaide Plains	0.7551***	0.0537	0.0072	0.0299	0.0295	254	0.9840
Barossa Valley	0.9318***	0.0341	0.0917**	0.0356	1.3446	181	0.9988
Clare Valley	0.8269***	0.1039	0.0556	0.0374	0.3215	214	0.9982
Coonawarra	0.8256***	0.0681	-0.0432	0.0660	-0.2476	154	0.9969
Eden Valley	0.7202***	0.0475	0.0473	0.0521	0.1690	207	0.9960
Langhorne Creek	0.8150***	0.0946	0.0705	0.0520	0.3809	228	0.9961
McLaren Vale	0.8755***	0.0532	0.0786*	0.0380	0.6310	233	0.9987
Padthaway	0.8571***	0.0803	0.0163	0.0330	0.1142	199	0.9934
Riverland	0.8798***	0.0178	0.0580***	0.0202	0.4821	345	0.9981
Wrattonbully	0.7555***	0.0483	0.0208	0.0199	0.0851	129	0.9947

Notes: *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Robust standard errors clustered at the variety level. Variety fixed effects and constants omitted to save space. 'LR coeff.' stands for long-run coefficient.

Apart from the (not statistically significant) negative coefficients of Coonawarra, the short- and long-run supply elasticities are in line with the results of model (10). They also have similar ranges to those observed in the analysis of Alston et al. (2015) for five regions of California.

Model (10) shares many of the above-mentioned limitations of model (9). Overall, these Nerlovian partial adjustments models only explain part of the changes in the mix of winegrape varieties. Further, the characteristics of perennial crops suggest that growers may adjust towards the desired area planted to a given variety more slowly than in annual crops, as they may delay their planting or replanting decisions. These limitations justify other types of analyses, even if these analyses rely less on econometric techniques and more on the use of more basic but holistic analyses of descriptive statistics (such as the ones presented in Section 3). This is even more relevant in our study, as the data on total plantings are only available for South Australia.

7. Conclusion

Australia's varietal mix has gone through dramatic changes, showing a tendency to become more concentrated and similar to that of the world as a whole, favouring some key French varieties. Part of the similarities across regions in their varietal mix may be explained by their climates and the characteristics of their production systems. However, climatic similarities do not seem to play a fundamental role in the degree to which regional mixes are becoming more or less similar.

Our supply response models show that prices and gross revenues per hectare explain part of the changes in the varietal mixes of South Australia's regions. The short-run price and revenue elasticities (as well as *relative* price and revenue elasticities) are between 0.074 and 0.089, while their long-run counterparts are between 0.333 and 0.397. These differences between short- and long-run elasticities, and their smallness as compared with supply response elasticity estimates for annual crops, are expected since viticulture is a very capital-intensive activity with decades-long investment horizons. They are consistent with the smallness of changes in acreages observed from year to year and the very long and slow processes of adjustment to prolonged changes in profitability in the industry.

While these models are less than ideal, they are quite useful considering the lack of data on costs for calculating net revenues per hectare, as well as on alternative crops or land uses. For perennial crops, when reliable data on new plantings and removals by variety and region become available, they would allow more powerful supply response models to be estimated. Further, other variables that influence what vignerons plant are often related to growers' behaviour or technical/investment issues such as differences in planting costs across varieties.

Despite the limitations of our supply response models, our analysis shows an important insight: the changes in varietal mixes seem more motivated by expected revenues than by what may grow best for the climate of each region. In the long run, these changes may lead to Australia producing lower-quality wine, since winegrape varieties are often planted in regions that are too warm for producing high-quality wine (Puga et al., 2022b). This situation may worsen in the wake of climate change and with global wine demand shifting towards more premium wine.

Future research could go beyond the analysis at the regional level to try to understand the variables influencing planting decisions at the individual vigneron level. Importantly, future research could also look at whether current policies are influencing vignerons' planting decisions in a way that is leading to varietal choices that may not be optimal for the climate of each region.

8. Acknowledgements

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Table A.1: Varietal similarity index (VSI), varietal concentration index (VCI), and area of each Australian region and state, and for the country as a whole.

Region	2001	2022	2001	2022	2022-2001	2022-2001	Area (ha)
	VSI	VSI	VCI	VCI	ΔVSI * 100	ΔVCI	2022
Adelaide Hills	0.48	0.55	14.4	15.9	7	2	3607
Adelaide Plains		0.55		20.8		21	374
Alpine Valleys	0.56	0.51	15.5	12.9	-5	-3	272
Barossa Valley	0.39	0.41	20.1	44.9	2	25	11445
Beechworth	0.44	0.58	18	13.8	14	-4	140
Bendigo	0.33	0.56	35.1	25.3	23	-10	631
Big Rivers - other	0.41	0.6	13.1	22.1	19	9	605
Blackwood Valley	0.5	0.6	17.6	18.7	10	1	314
Canberra District	0.47	0.61	14.6	16	14	1	318
Central Ranges - other	0.46	0.64	34.1	22.2	18	-12	390
Central Victoria - other	0.44	0.4	18.6	47.5	-4	29	190
Clare Valley	0.43	0.52	18.6	23.2	9	5	4973
Coonawarra	0.43	0.59	34.1	44.7	16	11	5479
Cowra	0.4	0.56	20.2	28.2	16	8	930
Eden Valley	0.33	0.51	21.8	21.3	17	0	2195
Fleurieu - other	0.42	0.64	21.2	20.2	22	-1	1820
Geelong	0.35	0.4	20.7	25.4	4	5	464
Geographe	0.48	0.66	16.8	14.3	18	-2	788
Gippsland	0.42	0.47	17.8	22.6	5	5	216
Glenrowan		0.54		23.6		24	202
Goulburn Valley	0.44	0.64	16.9	14.5	20	-2	1211
Grampians	0.35	0.37	26.9	54.4	2	28	634
Granite Belt	0.45	0.63	11.7	9.1	18	-3	351
Great Southern	0.48	0.62	15.5	18.7	15	3	2415
Greater Perth - other	0.36	0.54	10	21.4	19	11	168
Gundagai		0.56		32.7		33	635
Hastings River	0.38	0.22	15.6	22	-16	6	24
Heathcote		0.46		31.3		31	1686
Henty	0.36	0.36	16.2	24.3	0	8	159
Hilltops	0.43	0.59	23.2	29.9	16	7	591
Hunter Valley	0.33	0.44	20.9	19.2	11	-2	2622
Langhorne Creek	0.45	0.62	30.7	27.8	17	-3	5864
Limestone Coast - other	0.48	0.7	25.4	21	23	-4	3273
Macedon Ranges		0.49		20.7		21	141
Manjimup		0.56		20.3		20	162
Margaret River	0.49	0.67	15.8	16.5	17	1	5592
McLaren Vale	0.45	0.47	21	36.7	1	16	7160
Mornington Peninsula	0.3	0.31	25.8	38.4	1	13	901
Mudgee	0.44	0.69	22.6	17.1	25	-5	1909
Murray Darling - Swan Hill (NSW)	0.37	0.69	13.6	11.1	32	-2	7028

Murray Darling - Swan Hill (Vic)	0.26	0.66	16.7	14.6	40	-2	8699
North East Victoria - other	0.53	0.72	12.4	8.7	18	-4	1421
Northern Rivers - other	0.39	0.27	13.9	52.7	-12	39	7
Northern Slopes	0.41	0.7	20.4	13.4	30	-7	162
Orange	0.45	0.71	20.5	13.6	26	-7	1061
Padthaway	0.45	0.65	17.1	21.9	20	5	3608
Peel		0.62		19		19	63
Pemberton		0.4		30.6		31	469
Perricoota	0.49	0.6	18.9	18.8	11	0	459
Perth Hills	0.35	0.53	13.3	17.5	18	4	157
Port Phillip - other	0.38	0.66	14.8	23.1	29	8	520
Pyrenees	0.39	0.61	19.7	19.6	22	0	878
Qld - other	0.24	0.49	32.9	24.2	25	-9	83
Riverina	0.41	0.64	12.3	11.1	23	-1	17108
Riverland	0.47	0.65	12	16.2	19	4	19850
Rutherglen	0.29	0.37	19.5	18.2	7	-1	790
SA - other	0.32	0.51	36.3	26.7	19	-10	956
South Burnett	0.42	0.49	16.2	26.4	7	10	237
South Coast - other	0.45	0.7	15.8	9.6	25	-6	104
Southern Highlands		0.26		33.2		33	247
Southern New South Wales - other	0.38	0.57	19.3	25.4	19	6	46
Strathbogie Ranges		0.52		20.1		20	536
Sunbury	0.41	0.53	19	31.7	12	13	134
Swan District	0.37	0.4	9.5	13.7	2	4	893
Tasmania	0.34	0.34	21.4	29.9	0	8	2069
Tumbarumba	0.31	0.39	30.1	28.5	8	-2	219
Upper Goulburn		0.53		14		14	368
WA - other	0.51	0.73	12.1	11.6	22	0	81
Western Plains	0.44	0.58	20.6	21.6	13	1	236
Western Victoria - other	0.46	0.68	19.7	17.2	22	-2	62
Wrattonbully	0.43	0.64	35.7	31.2	21	-5	2617
Yarra Valley	0.44	0.46	19.8	24.4	1	5	2478
AUSTRALIA	**0.47**	**0.66**	**12**	**15.5**	**20**	**4**	
SA	0.46	0.62			16		
NSW	0.44	0.66			22		
Vic	0.37	0.66			29		
WA	0.5	0.68			18		
Tas	0.34	0.34			0		
Qld	0.4	0.58			17		

Source: Authors' compilation based on data in Anderson sand Puga (2923a).

Table A.2: Estimation results of a variation of model (9) in which one of the explanatory variables is the lag of the gross revenue per hectare of variety v in region r ($\ln\text{Revenue}_{vr,t-1}$) instead of $\ln\text{Price}_{vr,t-1}$.

Variable	Coefficient	Standard error
$\ln\text{Revenue}_{vr,t-1}$	0.0744***	0.0186
$\ln\text{Area}_{vr,t-1}$	0.7741***	0.0467
$\ln\text{Area}_{vr,t-2}$	0.0027	0.0372
Constant	-0.1407	0.1904
Time fixed effects	Yes	
Variety-by-region fixed effects	Yes	
R^2	0.9939	

Notes: *** denotes statistical significance at the 1% level. Robust standard errors clustered at the variety-by-region level.

Table A.3: Estimation results of a variation of model (9) in which one of the explanatory variables is the lag of the price of variety v in region r relative to the average price of all varieties sold in that region and year ($\mathrm{lnRelativePrice}_{vr,t\text{-}1}$) instead of $\mathrm{lnPrice}_{vr,t\text{-}1}$.

Variable	Coefficient	Standard error
$\mathrm{lnRelativePrice}_{vr,t\text{-}1}$	0.0888***	0.0211
$\mathrm{lnArea}_{vr,t\text{-}1}$	0.7726***	0.0466
$\mathrm{lnArea}_{vr,t\text{-}2}$	0.0038	0.0373
Constant	0.5466***	0.0689
Time fixed effects	Yes	
Variety-by-region fixed effects	Yes	
R^2	0.9939	

Notes: *** denotes statistical significance at the 1% level. Robust standard errors clustered at the variety-by-region level.

Table A.4: Estimation results of a variation of model (9) in which one of the explanatory variables is the lag of the gross revenue per hectare of variety v in region r relative to the average revenue per hectare of all varieties sold in that region and year ($\text{lnRelativeRevenue}_{vr,t\text{-}1}$) instead of $\text{lnPrice}_{vr,t\text{-}1}$.

Variable	Coefficient	Standard error
$\text{lnRelativeRevenue}_{vr,t\text{-}1}$	0.0864***	0.0202
$\text{lnArea}_{vr,t\text{-}1}$	0.0774***	0.0465
$\text{lnArea}_{vr,t\text{-}2}$	0.0027	0.0372
Constant	0.5641**	0.0684
Time fixed effects	Yes	
Variety-by-region fixed effects	Yes	
R^2	0.9939	

Notes: *** denotes statistical significance at the 1% level. Robust standard errors clustered at the variety-by-region level.