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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
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How Can We Use Econometrics to Assess Climate Impacts on the Wine Industry?

Germán Puga[1,2]*, Kym Anderson[2,3]

[1] Centre for Agricultural Economics and Development, University of Western Australia, Perth, WA 6009, Australia

[2] Wine Economics Research Centre, University of Adelaide, Adelaide, SA 5005, Australia

[3] Arndt-Cordon Department of Economics, Australian National University, Canberra, ACT 2601, Australia

*Corresponding author: german.puga@uwa.edu.au

Abstract

Winegrape production is very susceptible to weather conditions, with climate change presenting significant risks to the industry. Econometric analyses can offer valuable insights into the effects of past weather and climates, and of potential future climate changes. While econometrics is not the only method for deriving such insights, there is considerable potential for its application, especially given the rich (often underutilized) datasets available to the wine industry. Our article offers recommendations on how to effectively use econometrics to assess climate impacts on the wine industry. These recommendations are tailored to the specific characteristics of grape and wine production. We first discuss how to apply econometrics to assess the influence of weather or climate on wine-related outcomes. We provide insights into how to model weather and climate, avoid omitted variable bias, and address other modelling challenges. Finally, we explain how estimates of weather or climate impacts can be used to assess the potential effects of future climate change on the wine industry, providing valuable insights for the development of winegrape growers' adaptation strategies.

Keywords: grape growing, wine production, weather, climate change, physical risks, adaptation

1. Introduction

The weather has a prominent role in grape growing and hence in the yield and quality of wine produced (Geppert et al., 2024). While climate change may have a positive economic impact in cooler regions (Ashenfelter and Storchmann, 2010, 2016), the opposite may be true for warmer regions. Most of the world's wine production takes place in regions that are often too warm to produce high-quality wine from the most widely planted grape varieties (Puga et al., 2022a). In this context, econometric studies assessing climate impacts can help guide policies and strategies for winegrowers to adapt to future changes in climates.

Econometrics is not the only approach to assessing climate impacts on the wine industry. Recent machine learning models are often useful for this purpose thanks to their predictive capabilities (Maimaitiyiming et al., 2019). Techniques that combine inference and prediction (see Daoud and Dubhashi (2023)) offer the potential for wine economists to provide high-quality climate change impact assessments. Crop simulation models can incorporate environmental factors rarely observed in actual growing conditions that are difficult to model with other types of statistical analyses (Antle and Stöckle, 2017).[1] Experiments are also useful for identifying the impact of climate variables. Another less data-driven approach consists of relying on the opinion of experts.[2]

Econometric analyses have the advantage of relying on data from actual winegrowing conditions, capturing growers' actions and genuine responses to climatic circumstances. These conditions can differ from those in controlled settings (Blanc and Reilly, 2017). Given the wealth of data that is often available for the wine industry, it is possible to econometrically estimate the effect of weather or climate on an outcome. These models can lead to useful insights for the wine industry, often at a lower cost than when using other approaches such as field experiments. However, applying econometrics to quantify climate impacts on the wine industry requires considering a few aspects specific to the industry.

The aim of this article is to outline how to best use econometrics to assess climate impacts on the wine industry. More specifically, we recommend how to estimate the impact of weather, climate, and future climate changes on grape and wine production.[3] In doing so, we do not intend to update past surveys of the impacts of climate change on wine-related outcomes such as that by Ashenfelter and Storchmann (2016), nor to analyze how climate change is and will be impacting the industry (see Santos et al. (2020) and van Leeuwen et al. (2024) for reviews on that topic).

The structure of the rest of this article is as follows. Section 2 explains how to use econometrics to estimate the effect of weather or climate on a wine-related outcome. Section 3 provides important considerations when using those estimates to quantify future impacts of climate change. Last, section 4 concludes.

2. Estimating the Impact of Weather or Climate

It is possible to estimate the impact of weather or climate on a wine-related outcome by regressing that outcome on a set of weather or climate variables. Weather refers to atmospheric conditions

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[1] Crop simulation models can sometimes simulate conditions that have not yet been observed, such as extreme weather events. Yang et al. (2022) summarize crop simulation models and provide examples of cases where such models have been used successfully to study the impact of climate change on wine-related outcomes.

[2] While some economists such as Pindyck (2013, 2017, 2019) strongly argue for the use of these methods, others such as Auffhammer (2018) are more cautious and less excited about their potential. Various frameworks for measuring expert opinion have a strong potential in wine economics. One of these frameworks is the classical method, which can provide quantitative estimates of climate risks (Colson and Cooke, 2018).

[3] When looking at future climate impacts, this article focuses only on physical risks. These risks relate to the direct impacts of climate change on the grape and wine industry. This article does not give attention to transition risks, which are linked to the process of mitigating climate change by shifting towards a lower carbon economy due to factors such as changes in regulations and market demand.

during a short period, such as a growing season. Climate is the long-term average of those conditions over an extended period, often spanning decades.

The dependent variable of the econometric model is an outcome of interest. Examples of wine-related outcomes that are common in the wine literature are grape yields (e.g., Puga et al. (2023)), grape production (e.g., Quiroga and Iglesias (2009)), wine production (e.g., Niklas (2018)), wine prices or quality (e.g., Ashenfelter (2012) and Oczkowski (2016)), increases in alcohol concentration (e.g., Alston et al. (2011) and Godden et al. (2015)), and advancements in harvest dates (e.g., Jarvis et al. (2019)).

Such an econometric model can be estimated with cross-sectional, panel, or time series data. While a few interesting studies rely on very long time series datasets, often spanning centuries (e.g., Bock et al. (2013)), most studies rely on either cross-sectional or panel data. That is also the case in the broader climate econometrics literature.

2.1. Choosing Weather or Climate Variables

Viticulture is affected by a wide range of weather variables that can have different effects throughout the year. Table 1 provides a very simplified summary of how weather interacts with grapevine development and the timing of those developments (i.e., phenological growth stages). Yet even trying to account in a simplified way as to how weather affects the yield and quality of grape production can lead to a large number of independent variables in an econometric model. This is why most studies in the climate econometrics literature rely on just a few weather or climate variables. Also, including many correlated independent variables can make it difficult to interpret their coefficients because these variables are likely to absorb explanatory power from each other.

Table 1. Positive and negative weather influences on grapevine development and phenological growth stages. Adapted from Jones at al. (2012) and van Leeuwen et al. (2024).

Phenological stage	**Temperature**	**Insolation**	**Wind**	**Precipitation**
Dormancy	+ enough chilling hours to ensure full dormancy and subsequent bud development - very low temperatures can damage latent buds			+ sometimes needed to recharge soil moisture - too much soil moisture can delay leaf fall - heavy rainfall can lead to soil erosion
Vegetation development	+ average temperatures higher than 10°C tend to favor plant growth - very cool periods after budbreak slow growth - early frosts can reduce yield	+ need enough for flower differentiation - too little can lead to incomplete flowering	- can break shoots and even small branches	+ adequate levels of soil moisture are needed for proper development - too much soil moisture can lead to excessive vegetative growth - long wet periods can reduce or retard bloom - hail can damage leaves, shoots and flowers
Berry development	+ sufficient heat accumulation is needed for berry growth + appropriate diurnal temperature range is	+ enough needed for berry set + appropriate level needed for sugar accumulation	- can dehydrate berries	+ adequate levels of soil moisture are needed for proper development and to reduce heat stress

	needed for synthesis of sugars and tannins - high temperatures can lead to heat stress - late frosts can reduce yield			+ dry periods favor ideal photosynthesis, ripening, and balance - too much soil moisture can lead to excessive vegetative growth and limit ripening - high levels of rainfall favor diseases and can dilute berries - hail can damage berries and exacerbate the impact of diseases

The appropriate weather variables often depend on the region. Indeed, the expected effect of the different weather variables can be subject to various characteristics of the region, including its climate. For example, the impact of higher temperatures has long been associated with higher-quality wines in temperate regions such as Bordeaux (Ashenfelter, 2012; Ashenfelter et al., 2009), but the opposite effect is expected in most hotter wine regions such as in Australia (Puga et al., 2022b). The variety of climates across regions, sometimes within the same country, can make it difficult to come up with an econometric model appropriate for all the regions within a study.

Besides depending on the region, the expected impact of weather or climate on an outcome often depends on the grape variety. Figure 1 shows the optimal growing season temperature range for producing high-quality wine of some of the most widely planted varieties, according to Jones et al. (2012). While there is debate about these temperature ranges (van Leeuwen et al., 2013), this figure gives an indication of how much the impact of weather on grape production differs across varieties.

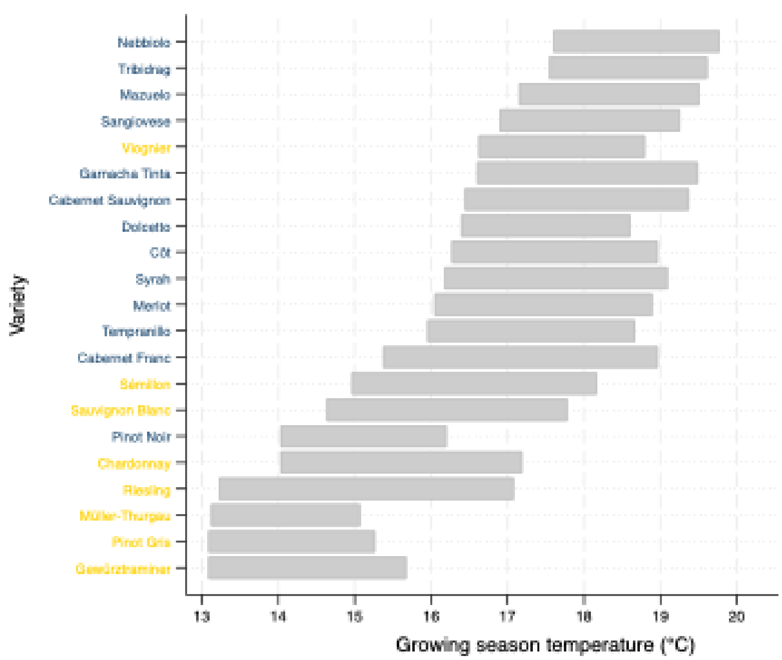

Figure 1. Ideal growing season temperature ranges for high-quality wine production according to Jones et al. (2012). Red varieties are in blue and white varieties are in yellow. Authors' compilation based on data from Jones et al. (2012).

Discriminating weather or climate impacts by region or variety is often difficult, as this would require a very large number of observations. Such large numbers are common for some broad-acre crops, but are not commonly available in grape and wine datasets.

A widely used functional form for capturing non-linear weather or climate effects implies adding a squared term to a weather or climate variable of interest. This leads to different estimated marginal effects of that variable, depending on the value of the variable itself. For example, an increase in the value of growing-season temperature can change from being beneficial in cool regions to being detrimental in hot regions.

When using panel data, a perhaps more interesting approach consists of estimating the effect of exposure to different levels of temperature. Schlenker and Roberts (2009) pioneered this approach to estimate the effect of temperature exposure to different temperature intervals on the yield of broadacre crops, showing that yield increases gradually as temperatures rise but decreases sharply once temperatures exceed about 30°C. This specification allows for capturing the impact of extreme temperatures and can be used in wine applications. Smith and Alston (2024) employ a method that quantifies the impact of growing degree days at various temperature thresholds, enabling a more accurate assessment of the effects of temperature extremes.

By assuming that temperature follows a sine curve between the minimum and maximum daily temperature, it is possible to estimate similar models as long as there is information on minimum and maximum daily temperature (Ortiz-Bobea, 2021). That leads to the computation of a growing degree days variable that is different from those often used in wine research, which are based on the difference between the average daily temperature and a cut-off value (e.g., 10°C). More recently, Ortiz-Bobea et al. (2019) introduce a method to look at different effects of temperature throughout the growing season.

In addition to the above-mentioned semiparametric models, there have been more recent developments using nonparametric functions. For instance, Schuurman and Ker (2025) estimate nonparametric models to account for nonlinear effects of weather across the yield distribution. Machine learning techniques such as neural networks can be useful for this purpose. Some of these methods, however, may require sample sizes that are uncommon in the wine industry.

That said, one benefit of wine-related data is that information is commonly available at the varietal level. In such instances, it becomes feasible to estimate a model in which the dependent variable is the outcome by variety, region, and year, rather than simply the regional outcome by year. As well, there are many wine databases with large sample sizes. This leads to a large number of observations, hence more degrees of freedom.

2.2. Avoiding Omitted Variable Bias

There are other variables that influence wine-related outcomes in addition to weather or climate variables. When using cross-sectional models, it is important to account for those other relevant variables to avoid biased estimates of the impact of climate on an outcome. The Ricardian model, first proposed by Mendelsohn et al. (1994), provides a theoretical framework that can be used for partially dealing with omitted variable bias in cross-sectional models (see Mendelsohn and Massetti (2017) for a review). This type of model has been used in wine applications when looking at the impact of climate on vineyard prices (e.g., Cross et al. (2011, 2017)).

There are also other ways of decreasing the potential for omitted variable bias in a cross-sectional model. For example, Puga et al. (2022b) use a survey on 103 viticultural practices of various wine regions of Australia to assess more precisely the impact of temperature on grape prices, by accounting for those practices.

By contrast, panel data models include fixed effects to account for certain unobserved factors that might otherwise bias the results (Deschênes and Greenstone, 2007). The basic idea behind fixed effects is that, by controlling for characteristics that do not vary by unit of observation (e.g., region) or by time (e.g., year), it is possible to identify the impact of the variables of interest more accurately.

For example, in a panel data model in which the unit of observation is a region, the region fixed effects attempt to capture all time-invariant observable and unobservable characteristics of each region. That includes the time-invariant component of the climate.[4] As a result, assuming the weather is appropriately represented, there is often less potential for omitted variable bias than in cross-sectional models.

However, omitted variable bias could still persist in panel data models thanks to time-varying variables. It is possible to control for those time-varying variables in the model, but these variables should be strictly exogenous (Dell et al., 2014). For example, if grape yield is the outcome variable, controlling for irrigation may be problematic because the season's weather influences how much growers irrigate their vineyard. Instead, controlling for other related variables such as water prices may sometimes be preferable.

Adding time fixed effects to panel data models allows for a further decrease in the potential for omitted variable bias. These fixed effects account for time shocks that affect all regions in a given year. While there is still potential for omitted variable bias due to region-specific time-varying variables, this potential is lowered by using time fixed effects.

It may be tempting to interact groups of regions with time fixed effects as a way to account for time shocks that are common to a group of regions. However, these group-specific fixed effects can absorb a great amount of the weather variance, so that the residual variance in the data consists primarily of noise (Fisher et al., 2012). Weather data are commonly subject to measurement error. This error is least when the focus is restricted to the specific area in which the vineyards are planted.

2.3. Other Modelling Issues

[4] The climate may have already been changing during the observed period. Fixed effects cannot capture a changing climate or other structural changes that may be underway.

There are other important econometric considerations in addition to the ones mentioned above. One such consideration implies choosing whether to estimate variables as levels or as logs. In the climate econometrics literature, the dependent variable is usually specified in its natural logarithmic form. Such a specification has advantages such as mitigating issues of heteroskedasticity, and handling outliers or extreme values, by reducing the variable's range (Wooldridge et al., 2021). Perhaps more importantly, this specification implies that the weather variables have the same proportional impact on a wine-related outcome across observations (e.g., regions).

While most studies model the weather or climate variables in levels (Camargo and Hsiang, 2015; Hsiang, 2016), it may be preferable to model the weather variables in their natural logarithms in some cases. For instance, when it seems more reasonable to assume constant elasticities for a non-negative weather variable.

When working with panel data, another important econometric consideration involves choosing whether to estimate a dynamic model, i.e., one incorporating a lagged dependent variable as an independent variable, rather than a static model. When estimating yields, most studies do not include the lag of this variable in their models. An exception is Chavas et al. (2019), who argue that a dynamic approach is justified because of the dynamics of crop fertility and management. Since grapevines are perennials, weather can influence grape production in more than one season (Molitor and Keller, 2017), adding another reason that might justify a dynamic model. However, modelling this is difficult due to the complex ways in which carbon is moved and allocated throughout the vine over the years.

In other cases, such as when modelling grape or wine prices, choosing whether to add a lag of the dependent variable can be more straightforward. The inclusion of a lag of grape or wine price in a model may be justified because the previous and current year prices can be linked through year-to-year changes in wine stocks.

To avoid biased estimates in dynamic models, it is possible to use the system generalized method of moments (system GMM) estimator developed by Arellano and Bond (1991). This is an example of a case in which other estimators may be more appropriate than the fixed effects estimator, which is the most commonly used estimator in panel data models (Blanc and Schlenker, 2017).

The estimation strategy and choice of estimator are also very relevant and can influence the way the estimates should be interpreted. When estimating a cross-sectional model using average weather (or climate data), the impact of climate is estimated. Instead, when using panel data, what is estimated is the impact of weather. If the model is estimated using the fixed effects estimator (the commonly used estimator in panel data models), what is estimated is the impact of weather shocks (Blanc and Schlenker, 2017). These denote differences from the mean weather, and they are considered random and exogenous.[5]

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[5] This consideration can be controversial because grape growers often have expectations of the future weather of the growing season. For example, they may know what may likely be expected based on the El Niño-Southern Oscillation (ENSO). Nevertheless, from a practical perspective, the main concern regarding ENSO should be whether the number of years is sufficiently large.

Another important econometric consideration involves dealing with spatial autocorrelation. When the data are available by wine regions, which are well delimited and distanced from each other, there may be less need to account for spatial autocorrelation. Still, even in those cases, not accounting for this type of autocorrelation could result in overly confident estimates. Ortiz-Bobea (2021) provides a well-grounded discussion on how to deal with spatial autocorrelation in climate econometrics.

3. Quantifying Future Impacts of Climate Change

The estimates of the impact of weather or climate from an econometric model can be used to quantify the potential consequences of climate projections. This implies using past observations to predict how climate change will affect a wine-related outcome in the relatively distant future. Therefore, the main limitation of this approach is that it assumes a ceteris paribus scenario, i.e., one in which only the climate is considered to change.

Beyond the uncertainty related to variables that could change in the future other than climatic ones, there is statistical uncertainty surrounding the estimates and also uncertainty in the climate change projections. To deal with this last type of uncertainty, using different climate change projections and emission pathways is good practice (Burke et al., 2015).

A potential issue involves extrapolating outside the range of values observed in the dataset. Puga et al. (2023) show that in their dataset some of the climate projections for the end of this century (the orange diamonds in Figure 2) are too different from those in their data (the black circles), but that does not seem to be a problem with the mid-century climate projections (the green squares). Hence those authors focus only on the mid-century climate forecasts.

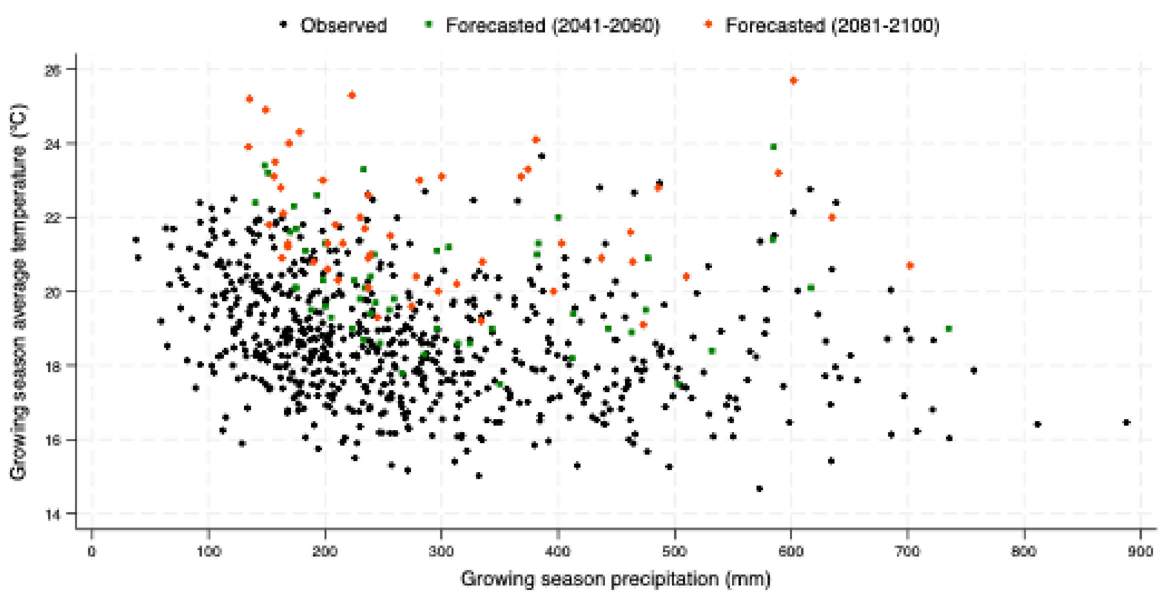

Figure 2. Growing season temperature and precipitation for the observed weather values in the major Australian wine regions, and for the climate projections for those regions for 2041-2060 and 2081-2100. Authors' compilation based on data from Puga et al. (2023) and climate projections from Remenyi et al. (2020).

More uncertainty relates to the differences between what data are observed historically and what are not observed but may occur in the future. Part of that uncertainty is difficult to avoid. An example is the impact of carbon fertilization, which cannot be accounted for since the future levels of carbon dioxide (CO_2) in the atmosphere are expected to be higher than at present (and in the past).

Another example of an issue that may not be recorded in the data relates to increasingly common climatic events. This is arguably more relevant for grapevines than for annual crops because of the perennial characteristics of grapevines. Since yields form over two consecutive seasons, the weather in one season influences both the current and the following season (Guilpart et al., 2014). For instance, two consecutive years of drought may have a greater negative impact than two drought of equal severity spread over non-consecutive years.

Using the estimates of a panel data model usually raises another important issue: not accounting for the impact of long-run adaptation of already available technologies. This is because a panel data model estimates the impact of weather shocks on an outcome. Winegrowers change practices such as irrigation and winemaking techniques based on each season's weather. Those short-run adaptation options are captured in the estimates of the impact of weather shocks, but what is not captured are the changes in production strategies resulting from long-run changes in climates. Some of those adaptations will likely take place in the vineyards and wineries (Naulleau et al., 2022; Santos et al., 2020).

In the case of wine, long-run adaptation might be less important due to the strong associations between grape varieties and production characteristics with specific regions often identified by geographic indications (GIs), such as Protected Designations of Origin (PDOs) in Europe. These designations not only protect the product's reputation but can regulate the production technology as well (Meloni et al., 2019). As a result, wine production is less flexible than for many other crops, both in terms of where it takes place and how it is produced, even over the long run, primarily due to marketing considerations.

That being said, in recent years, researchers have developed hybrid methods that rely on the cross-sectional features of panel datasets for capturing long-run adaptation (see Kolstad and Moore (2020) for a review). These approaches include long differences (e.g., Moore and Lobell (2015)), partitioning variation (e.g., Moore and Lobell (2014), Burke and Emerick (2016)), and panels with heterogeneous marginal effects (e.g., Butler and Huybers (2012)). Despite the possibility of getting plausible results without taking long-run adaptation into account in the wine sector, these recently introduced hybrid methods could lead to powerful insights.

4. Conclusion

Econometric models can provide estimates of the effect of weather or climate on a wine-related outcome. Those estimates can be used to assess the potential impact of future climate changes. Importantly, econometric models should consider the specific nature of grape and wine production. Wine industry-specific considerations should also influence the way the estimates are used to assess future climate risks. While this article provides an incomplete list of considerations when assessing climate impacts, it provides some key insights into how to approach this issue.

We recognize that econometrics is not the only approach for assessing climate impacts on the wine industry. However, econometric analyses have numerous advantages over other approaches, such as capturing winegrowers' responses to climatic events. As well, many unexploited (often freely available) datasets can be used for econometric analyses of climate impacts. These analyses can be very helpful in shedding light on the impacts of weather and climate on the wine industry, and thereby in designing appropriate climate adaptation strategies.

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