The Impact of Temperature on Grape Prices: Evidence from Australia

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1. Introduction

The potential impact of climate change has motivated the Australian wine sector to fund the development of a Climate Atlas that provides information on how climate will change in the various Australian wine regions (i.e., Remenyi et al. (2019)). This Climate Atlas projects that precipitation patterns will change in different directions across wine regions, but temperatures will increase in all regions. The aim of this study is to estimate the impact of growing season temperature (GST) on grape prices in Australia and to quantify the potential impact of future changes in GST projected in the Climate Atlas. GST is the most widely used thermal-based bioclimatic index in viticulture and is highly related to grape quality (Liles and Verdon-Kidd, 2020).

There are two major econometric approaches to estimating the impact of weather or climate and climate change in agriculture: the cross-sectional approach and the panel data approach (Blanc and Schlenker, 2017). Panel data models have better identification properties and are less susceptible to omitted variable bias than cross-sectional models, but they estimate the impact of weather shocks rather than climate (Hsiang, 2016). Therefore, the estimates of panel data models do not account for medium- and long-term adaptation (Auffhammer, 2018).

In this study, there is an extra motivation for using a cross-sectional approach. Grape prices in Australia are usually reported before they are adjusted based on wine quality, and these quality adjustments are often influenced by the season's weather. If we would use a fixed effects panel data model to estimate the impact of GST on grape prices, we would be estimating the impact of GST shocks (weather shocks), and the effect of GST (climate) would be captured by the group fixed effects. Since grape prices are usually reported before they are adjusted due to the effect of GST among other variables, we may expect to get estimates of the impact of GST shocks that are not statistically significant. In fact, this is what happens in this particular case when we use a panel data approach. A cross-sectional approach allows us to avoid this issue by estimating the impact of climate instead of the impact of weather shocks.

The difference between our analysis and the ones of other researchers such as Webb et al. (2008) is that our model intends to control for 105 characteristics that may influence price and that may be correlated with GST. We do this by first performing a principal component analysis (PCA) for reducing the dimensionality of the data that relate to the production system of each region. Then we use principal components as control variables, which allows us to deal with omitted variable bias issues while avoiding problems of multicollinearity and overcontrol. As a robustness check, we use a LASSO model. This is, to our knowledge, the first cross-sectional analysis of the impact of a weather variable on grape prices that controls for numerous characteristics of the production system.

2. Data

We use data for Australia on average price by variety and region, average bearing area by variety and region, and average yield by region, from Anderson and Aryal (2015). These data are mostly available for 2001 to 2012, although we drop 2009 and 2011 as for those years there are no data on area and regional yield. For each region, and for the same time period, we obtain data on GST and growing season precipitation (GSP) from the Scientific Information for Land Owners (SILO) (Jeffrey et al., 2001), based on the area covered by the geographical indication (GI) of each region. We also use data on 103 characteristics of the production system of each region, from an Australian Wine Research Institute (AWRI) survey (Nordestgaard, 2019). Since our dataset includes 26 regions that have 33.1 varieties on average, the total number of observations is 861.

3. Estimation Strategy

For identifying the impact of GST on grape prices, we estimate:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \beta_1 GSP_r + \beta_2 Yield_r + \sum_{j=1}^{j=4} \varphi_j PC_{jr} + \mu_v + \varepsilon_{vr}. \qquad (1)$$

$lnPrice_{vr}$ is the natural logarithm of the average price of grape of variety v in region r across the time period. The variable of interest, GST_r, is the mean GST in region r in that same period. The control variables GSP_r and $Yield_r$ are the mean GSP and average regional yield, respectively, in region r, also for that same period. μ_v are variety fixed effects that control for price differences between varieties. α is a constant and ε_{vr} is an error term.

We use principal component analysis (PCA) for data reduction of the 103 variables from the abovementioned AWRI survey. The goal here is to use principal components as control variables that account for characteristics in the production system of each region. Based on the visual inspection of a scree plot (i.e., using the elbow rule), we incorporate the first four principal components, which explain 47% of the variance in the data and do not lead to issues of overcontrol and multicollinearity, as suggested by the analysis of the VIFs of the independent variables. If instead we would incorporate, for example, all the principal components with eigenvalues higher than 1, this would lead to issues of overcontrol and multicollinearity. Further, for inspecting how useful these first four principal components may be as a proxy of the production system of the regions, we use these components to perform a k-means cluster analysis of the 26 regions. The Calinski-Harabasz stopping rule suggests that six groups is the optimal solution. We believe that this six-group classification leads to groups with similar production systems and hence, that the first four principal components are useful for controlling for regional production system characteristics that may affect prices. In model (1), PC_{jr} is the j (out of 4) principal component of region r.

We use weighted least squares (WLS) for estimating model (1). The weight is the average area of variety v in region r during the time period. Since GST and the control variables are region-specific, we cluster standard errors by region. As a robustness check, we estimate the impact of GST on grape prices using LASSO. Specifically, we use the cross-fit partialing-out estimator, also known as double machine learning.

4. Results and Discussion

The results of model (1) show that GST and most control variables are statistically significant at the 5% or 1% level (see Table 1). These results suggest that a GST increase of 1℃ leads to a decrease of 9% in the average price of grapes. If we would not control for the characteristics of the production system using the four principal components, we would overestimate the effect of GST by 2.3 times. These differences show how cross-sectional estimations of the impact of climate on grape prices can be susceptible to omitted variable bias.

Table 1: Estimation results.

Variable	Model (1)
GST (growing season average temperature)	-0.0946**
	(0.0412)
GSP (growing season precipitation)	-0.0006***
	(0.0002)
Yield (average regional yield)	-0.0054
	(0.0057)
PC1 (principal component 1)	-0.0371**
	(0.0149)
PC2 (principal component 2)	0.0259**
	(0.0107)
PC3 (principal component 3)	-0.0544***
	(0.0118)
PC4 (principal component 4)	-0.0065
	(0.0055)
Constant	8.3806***
	(0.8101)
R^2	0.9402

Notes: * = 10% significance level, ** = 5% significance level, and *** = 1% significance level. Standard errors are in brackets. Model (1) includes variety fixed effects (results omitted to save space).

We use the results of model (1) to quantify the potential impact that changes in GST by 2050 could have on grape prices due to changes in quality, based on the projections from Remenyi et al. (2019). Assuming a *ceteris paribus* scenario, the price of grapes is projected to decrease by between 8.1% and 14.4% across regions, or 11.8% on average (see Figure 1). If we would not control for the characteristics of the production system using the four principal components, we would overestimate the effect of climate change by 114%. Besides illustrating the issue of omitted variable bias, these differences suggest that adaptations in the production system may help to mitigate some of the quality losses that may be induced by climate change.

Figure 1: Estimated decrease in the price of grape in continental Australia due to the impact of projected increases in growing season average temperature (GST) between 1997-2017 and 2041-2060, based on the climate change projections from Remenyi et al. (2019).

The LASSO model, which we use as our robustness check, uses 45 controls out of 126 potential controls incorporated in the model. GST is statistically significant at the 1% level, and its magnitude is slightly lower than in model (1): its coefficient value is -0.0759 and its standard error is 0.0295. The interpretation of this coefficient is that a GST increase of 1°C leads to a decrease of 7.3% in the price of grapes. These results reinforce our argument on the importance of controlling for variables that relate to the production system.

5. Conclusion

We have estimated the effect of GST on grape prices using cross-sectional data for Australia. Our results suggest that a GST increase of 1°C leads to a decrease of 9% in the average price of grapes and that by 2050, assuming a *ceteris paribus* scenario, climate change is expected to lead to a decrease in the price of grapes of 11.8% on average. Our results also show how price, due to changes in grape quality, is influenced by the production system, which in turn suggests that changes in the production systems may help reduce quality losses from climate change. From a statistical perspective, this study shows how PCA results can be used to control for numerous characteristics of the production system, reducing the susceptibility of cross-sectional analyses to omitted variable bias while avoiding issues of multicollinearity and overcontrol. LASSO models, such as the one that we have used as a robustness check, can also be used for getting estimates that are less susceptible to omitted variable bias. Further research could explore other variables affecting grape prices or quality, incorporate new control variables, and/or apply this or a similar approach to other countries.

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