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The Impact of Growing Season Temperature on Grape Prices in Australia

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Abstract

Cross-sectional models are useful for quantifying the impact that climate or climate change may have on grape prices due to changes in grape quality. However, these models are susceptible to omitted variable bias. The aim of this study is to estimate the impact of growing season temperature (GST) on grape prices using cross-sectional data for Australia, while controlling for growing season precipitation, regional yield, variety, and other 103 characteristics that relate to the production system of the wine regions. We estimate this model using (area) weighted least squares and variables from a principal component analysis (PCA) to control for the characteristics that relate to the production system. This estimation strategy allows us to decrease omitted variable bias while avoiding multicollinearity and over-controlling issues. We show that failing to control for characteristics that relate to the production system overestimates the impact of GST and hence, climate change. This finding is confirmed by a LASSO model that also incorporates variables from the PCA, which we estimate as a robustness check using a cross-fit partialing-out estimator (double machine learning).

Keywords: omitted variable bias, climate impact, grape quality, grape price, climate change

1. Introduction

Cross-sectional models allow one to quantify the impact that climate or climate change may have on grape prices due to changes in grape quality. Webb et al. (2008) studied the temperature-quality relationship in grapes in Australia using cross-sectional data. That study failed to control for variables that are correlated with the variable of interest and that may have an influence in the dependent variable, possibly leading to biased estimates of the variable of interest. This is a standard issue with cross-sectional models, as they are very susceptible to omitted variable bias. Panel data models, by contrast, have better identification properties and are less susceptible to omitted variable bias. However, panel data models estimate the impact of weather shocks rather than climate. These estimates do not account for adaptation and may be less useful when estimating the potential impact of climate change.

The aim of this study is to estimate the impact of growing season temperature (GST) on grape prices in Australia using cross-sectional data. GST is the most widely used thermal-based bioclimatic index in viticulture (Liles and Verdon-Kidd, 2020). While extreme temperatures can have a major influence on grape quality (Cola et al., 2019), GST is a useful bioclimatic index that is highly related to grape quality (Jones et al., 2011).

The difference between our analysis and the one of other researchers such as Webb et al. (2008) is that our models intend 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 the 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 for inference. 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 spatial data on temperature and precipitation from Scientific Information for Land Owners (SILO) (Jeffrey et al., 2001), based on the area covered by the geographical indication (GI) of each region. We construct two mean weather variables: growing season average temperature (GST), which is our independent variable of interest; and total growing season precipitation (GSP). While the length of the growing season varies between varieties and regions in Australia (Pearson et al., 2021), and also between years (Cameron et al., 2021, Jarvis et al., 2019), we define growing season as the period between October and April.

We also use data on 103 characteristics of the production system of each region, from an Australian Wine Research Institute (AWRI) survey (Nordestgaard, 2019). The first column of Appendix Table 1 lists these 103 variables. While the data on grape prices and weather variables is available for a larger number of regions, our estimation dataset includes 26 regions because those are the regions for which we have information from the AWRI survey. Table 1 shows summary statistics for the 26 regions in our dataset. Each variety-by-region combination constitutes an observation. Since the regions have 33.1 varieties on average, the total number of observations is 861.

Table 1: Summary statistics for the 26 regions.

Variable	Minimum	Mean	SD	Maximum
Price ($/T)	410	1198	462	2453
GST (℃)	14.2	18.3	1.7	21.6
GSP (mm)	155	323	128	569
Yield (T/ha)	3.1	7.8	3.8	20.7
Varieties	1	33.1	17.8	75

Notes: GST is the growing season average temperature, GSP is the growing season total precipitation, Yield is the average regional yield, and Varieties is the number of varieties.

3. Methods

The aim of our estimation strategy is to identify the impact of GST on grape prices. The baseline model is:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \mu_v + \varepsilon_{vr}, \tag{1}$$

where $lnPrice_{vr}$ is the natural logarithm of the average price 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, and γ is the coefficient of interest. μ_v are variety fixed effects that control for price differences between varieties. α is a constant and ε_{vr} is an error term.

However, model (1) is susceptible to omitted variable bias. Other climate variables and characteristics of the production system that influence price may be correlated with GST. Failing to include these variables can lead to an incorrect estimation of the effect of GST on the price of grape. Therefore, we estimate:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \beta_1 GSP_r + \beta_2 Yield_r + \mu_v + \varepsilon_{vr}. \qquad (2)$$

The control variables GSP_r and $Yield_r$ are the mean GSP and average regional yield, respectively, in region r, for the time period.

While model (2) incorporates two control variables (i.e., GSP_r and $Yield_r$), this model is still susceptible to omitted variable bias. Other characteristics of the production system that affect price are also correlated with GST. Ideally, we would like to incorporate the 103 variables from the AWRI survey that relate to the production system of each region. This is doable if we use principal component analysis (PCA) for data reduction. The goal here is to use the principal components as control variables that account for characteristics in the production system of each region. Therefore, we estimate:

$$lnPrice_{vr} = \alpha + \gamma GST_r + \beta_1 GSP_r + \beta_2 Yield_r + \sum_{j=1}^{j=k} \varphi_j PC_{jr} + \mu_v + \varepsilon_{vr}. \qquad (3)$$

PC_{jr} is the j (out of k) principal component of region r, and φ_j is its coefficient.

We use two approaches for choosing the number of principal components. First, we choose all the components with eigenvalues greater than one. Second, we look at a scree plot to choose the principal components. For inspecting how useful the principal components from this second step are, we use them to perform a k-means cluster analysis based on the Euclidean distance between observations. Then, we choose the optimal cluster solution based on the Calinski-Harabasz stopping rule. The intuition here is that if the classification looks reasonable, these first principal components may be suitable for accounting for characteristics of the production systems of the regions.

We use weighted least squares (WLS) for estimating models (1), (2), and (3). 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 use ordinary least squares (OLS) with robust standard errors clustered at the regional level.

In addition to the abovementioned models, as a robustness check, we estimate the impact of GST on grape prices using LASSO for inference. Specifically, we use the cross-fit partialing-out estimator, also known as double machine learning. The potential control variables that we incorporate in the model are GSP, regional yield, all the varieties, and all the components from the PCA that have eigenvalues greater than one.

4. Results

The results for models (1) and (2) show that the coefficients of GST are negative and statistically significant at the 1% level (see Table 2). The interpretation is that a GST increase of 1℃ leads to a decrease in price of 24% based on model (1), or 19.4% based on model (2). (GST impact in percentage = (EXP(GST coefficient)-1)*100). The coefficient of GST is of lower magnitude in model (2), after controlling for GSP and regional yields.

Table 2: Estimation results.

Variable	Model (1)	Model (2)	Model (3)
GST	-.2742***	-.2151***	-.0946**
	(.0243)	(.0321)	(.0412)
GSP		-.0006	-.0006***
		(.0004)	(.0002)
Yield		-.0349***	-.0054
		(.0082)	(.0057)
PC1			-.0371**
			(.0149)
PC2			.0259**
			(.0107)
PC3			-.0544***
			(.0118)
PC4			-.0065
			(.0055)
Constant	11.4275***	10.7362***	8.3806***
	(.4968)	(.6083)	(.8101)
R^2	0.8689	0.9117	0.9402

Notes: * = 10% significance level, ** = 5% significance level, and *** = 1% significance level. GST is the growing season average temperature (℃), GSP is the growing season total precipitation, Yield is the average regional yield, and PC stands for principal component. Models (1) to (3) include variety fixed effects (results omitted to save space).

Model (3) incorporates principal components from the PCA of the production systems of the regions. The PCA leads to 22 principal components with eigenvalues higher than one, which explain 98% of the variance in the data (see Figure 1). We estimate model (3) with the first 22 principal components as control variables. However, a post-estimation analysis of the variance inflator factors (VIFs) of the independent variables show strong evidence of multicollinearity with this specification.

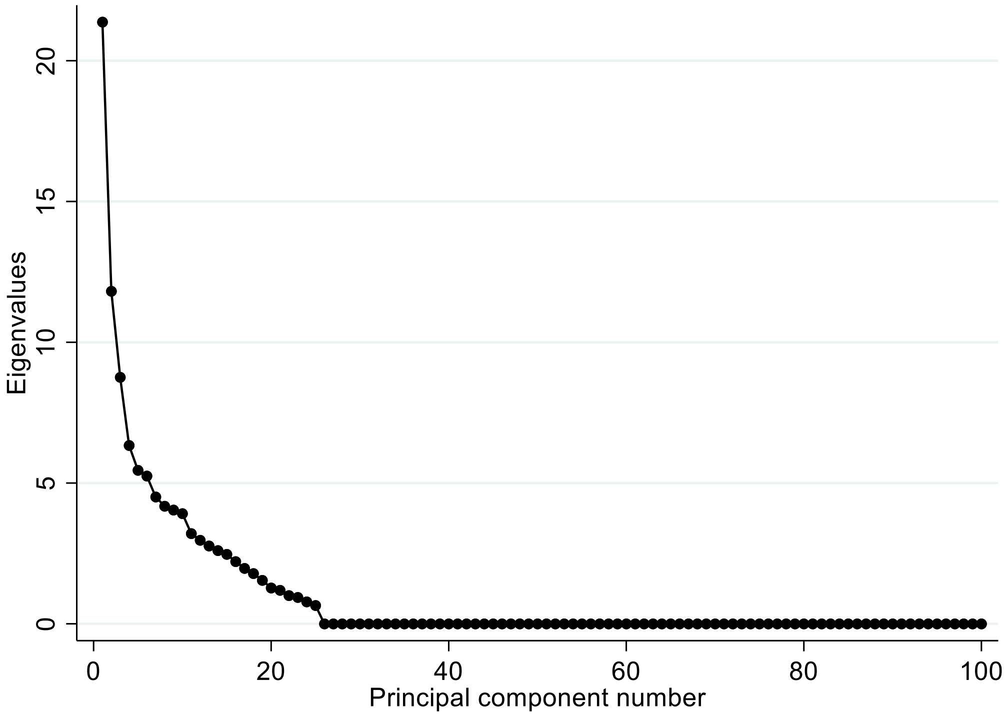

Figure 1: Scree plot of eigenvalues after PCA.

Therefore, we estimate model (3) by using only the first four principal components, which explain 47% of the variance in the data. The second column of Appendix Table 1 shows the percentage of each of the 103 variables that relate to the production system that is explained by the first four principal components. For this specification, the analysis of the VIFs of the independent variables suggest that multicollinearity is not an issue. 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 for clustering the 26 regions. The Calinski-Harabasz stopping rule suggests that six groups is the optimal solution for our k-means cluster analysis (see Table 3). We believe that this six-group classification looks plausible and hence, that the first four principal components are useful for controlling for regional production systems characteristics that may affect prices. The last seven columns of Appendix Table 1 show the average value of each of the 103 variables that relate to the production system, for each of the six clusters and for all the regions combined.

Table 3: Six-group classification based on the first four principal components.

Cluster	Regions
1	Beechworth, Geelong, Macedon Ranges, Mornington Peninsula
2	Barossa Valley, Clare Valley, Eden Valley, McLaren Vale, Mudgee, Rutherglen
3	Murray Darling, Riverina, Riverland
4	Coonawarra, Heathcote, Langhorne Creek, Wrattonbully
5	Great Southern, Hilltops, Hunter, Orange
6	Adelaide Hills, Granite Belt, Tasmania, Yarra Valley, Margaret River

The results of model (3) show that GST is statistically significant at the 5% level (see Table 2). The interpretation is that a GST increase of 1°C leads to a decrease of 9% in the average price of grapes. When compared to models (1) and (2), the magnitude of the GST coefficient is 2.9 and 2.3 times lower, respectively. The goodness of fit of model (3) is also higher than that of models (1) and (2). These results show how cross-sectional estimations of the impact of climate on grape prices can be susceptible to omitted variable bias. Our OLS estimations for these three models, which we use as robustness checks, also show that the magnitude of the GST coefficient is substantially lower for model (3).

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 (3): 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℃ 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. Discussion

The progression of the results from model (1) to model (3) shows the importance of controlling for variables other than region and variety when estimating the impact of weather on grape prices. The results from the LASSO model reinforces this idea. The cross-sectional approach to estimate the impact of climate is susceptible to omitted variable bias. This can be addressed, to a certain extent, by including control variables in the model. However, an excessive number of control variables can also lead to multicollinearity and over-controlling issues. This study shows how PCA can be used for dealing with these issues while still controlling for relevant variables in the model.

Nevertheless, while model (3) controls for GSP and characteristics of the production system, it still has at least four limitations. First, the estimate of GST may still be biased. This is because there are other characteristics that influence grape quality and that may be correlated with GST, but that are not accounted for in the model. Second, due to data limitations, the independent variables are based on regional characteristics rather than variety-by-region characteristics. Third, the impact of the weather variables may be nonlinear. We explore alternate model specifications, such as including square values of GST and/or GSP, but concluded that including only the levels is preferred. Fourth, model (3) assumes that the impact of GST on (the natural logarithm of) grape prices does not vary across regions or varieties.

In reality, the impact of GST may and differ across regions and varieties. To explore part of this possibility, we allow the effect of GST to vary for the three most planted varieties in Australia: Syrah, Cabernet Sauvignon, and Chardonnay. The coefficients are not statistically significant for Syrah and Cabernet Sauvignon, while the coefficient for Chardonnay is positive and statistically significant at the 5% level. Therefore, these results suggest that while an increase in GST leads to a lower price for Chardonnay, that change in price is smaller than for other varieties such as Syrah and Cabernet Sauvignon.

Despite the abovementioned limitations, model (3) provides a useful estimate of the potential impact that climate change may have on grape prices in a *ceteris paribus* scenario. Table 4 combines the results from the three models with the climate change projections from Remenyi et al. (2019), to quantify the potential impact that changes in GST by 2050 could have on grape prices due to changes in quality. Based on the estimates of model (3), the price of grapes is projected to decrease by between 8.1% and 14.4% across regions, or 11.8% on average. Assuming that the GST coefficient in model (3) is correct, using the estimates of models (1) or (2) would overestimate the impact of changes in GST by 166% or 114%, respectively. 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.

Table 4: Projected impact of forecasted changes in GSTs (between 1997-2017 and 2041-2060) on grape prices based on the estimates of the three models.

Region	GST (°C)		Projected impact (%)		
	1997-2017	2041-2060	Model (1)	Model (2)	Model (3)
Adelaide Hills	17.9	19	-26.4	-21.3	-9.9
Barossa Valley	19	20.3	-31.2	-25.2	-11.7
Beechworth	17.8	19.4	-38.4	-31.0	-14.4
Clare Valley	19.1	20.4	-31.2	-25.2	-11.7
Coonawarra	17.3	18.7	-33.6	-27.1	-12.6
Eden Valley	18.4	19.5	-26.4	-21.3	-9.9
Geelong	17.2	18.3	-26.4	-21.3	-9.9
Granite Belt	18.7	20.1	-33.6	-27.1	-12.6
Great Southern	18	19.5	-36.0	-29.0	-13.5
Heathcote	18.5	19.8	-31.2	-25.2	-11.7
Hilltops	19.5	21	-36.0	-29.0	-13.5
Hunter	20.2	21.4	-28.8	-23.2	-10.8
Langhorne Creek	19.2	20.1	-21.6	-17.4	-8.1
Macedon Ranges	16.2	17.5	-31.2	-25.2	-11.7
Margaret River	18.9	20.3	-33.6	-27.1	-12.6
McLaren Vale	18.6	19.8	-28.8	-23.2	-10.8
Mornington Peninsula	17.4	18.6	-28.8	-23.2	-10.8
Mudgee	19.5	20.9	-33.6	-27.1	-12.6
Murray Darling	21.9	23.2	-31.2	-25.2	-11.7
Orange	18.1	19.5	-33.6	-27.1	-12.6
Riverina	21.8	23.3	-36.0	-29.0	-13.5
Riverland	21.1	22.4	-31.2	-25.2	-11.7
Rutherglen	19.7	21.2	-36.0	-29.0	-13.5
Tasmania	14.4	15.6	-27.6	-22.3	-10.4
Wrattonbully	17.5	19	-36.0	-29.0	-13.5
Yarra Valley	16.3	17.5	-28.8	-23.2	-10.8
Average	18.5	19.9	-31.4	-25.4	-11.8

Notes: GST is the growing season average temperature. Estimated with the three models' results, based on climate change projections from Remenyi et al. (2019).

6. Conclusion

We have estimated the effect of GST on grape prices using cross-sectional data for Australia. Our results show how cross-sectional models can be susceptible to omitted variable bias. In particular, failing to control for characteristics of the production systems that are influenced by GST can overestimate the true impact of GST on grape prices. Our results also show how price, due to changes in grape quality, is influenced by the production system. This finding 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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Appendix

Appendix Table 1: Explained variance by the first four principal components, and average values for each cluster of regions and for the all the regions combined, for the 103 variables that relate to the characteristics of the production system of each region.

Variable	Explained (%)	Group of regions (average values)						
		1	2	3	4	5	6	All
Median age (years)	8	19	22	17	20	20	18	19
Median row spacing (m)	67	2.5	3.1	3.3	2.9	3.1	2.6	2.9
Median vine spacing (m)	66	1.5	1.9	2.1	1.8	1.7	1.6	1.8
Median plant density (vines/ha)	70	2839	1737	1451	1951	1950	2528	2091
Median row length (m)	56	118	208	293	259	191	158	199
Median row yield (kg/row)	85	117	417	2061	605	423	291	566
Single cordons	62	74	84	40	91	96	72	78
Multiple cordons	62	26	16	60	9	4	28	22
Row direction: N-S	47	64	49	33	45	62	59	53
Row direction: E-W	48	23	39	54	46	31	26	35
Row direction: NE-SW	35	0	2	10	6	4	10	5
Row direction: NW-SE	24	12	4	3	3	2	5	5
Row direction: contour	21	0	6	0	1	2	1	2
Post material: wood CCA treated	16	52	73	79	52	49	70	63
Post material: wood creosote treated	51	6	10	11	45	0	1	12
Post material: wood untreated	49	26	1	0	0	2	21	8
Post material: metal	66	15	15	9	1	49	8	16
Post material: plastic	22	2	1	0	3	0	0	1
Post material: other	17	0	1	0	0	0	0	0
Rootstocks	39	54	39	47	33	10	28	35
Pruning: cane	89	77	14	0	5	11	52	28
Pruning: spur	66	21	61	9	68	67	47	48
Pruning: mechanical	73	0	25	90	27	22	1	24
Pruning: minimal	11	2	0	0	0	0	0	0
Pruning wound treatment: local application	63	41	10	0	2	1	25	14
Pruning wound treatment: spray unit application	39	0	26	6	44	2	19	17
Sprays (average number)	40	9.7	7.2	7.7	7.0	8.8	9.5	8.3
Desuckering: hand	54	98	50	47	62	51	66	62
Desuckering: mechanical	5	0	14	0	2	1	0	4
Desuckering: chemically	56	1	15	33	5	39	15	17
Desuckering: other	6	1	6	0	1	5	4	3
Trims (average number)	21	0.8	1.1	1.0	1.2	0.9	1.5	1.1
Trellis system: VSP	77	72	25	10	49	72	94	55
Trellis system: SH SD	25	2	2	7	0	0	4	2
Trellis system: T-trellis	32	12	6	8	0	0	0	4

Trellis system: bush	19	0	1	0	0	0	0	0
Trellis system: other	26	13	1	6	1	0	1	3
Trellis system: sprawl	83	1	65	69	50	28	2	35
Shoot positioning: all shoots positioned	84	85	22	1	15	54	96	47
Shoot positioning: all shoots one side, some/none on other	23	0	1	1	22	3	2	5
Shoot positioning: other	24	0	1	0	0	0	0	0
Shoot thinned	77	80	18	1	18	16	51	32
Leaf plucking: both sides	49	5	0	0	1	7	23	6
Leaf plucking: one side	43	13	1	0	4	3	10	5
Leaf plucking: other	11	0	0	0	0	0	0	0
Irrigation method: drip or micro-spray	43	97	95	84	93	99	93	94
Irrigation method: spray or sprinkler	39	3	4	10	5	0	3	4
Irrigation method: furrow or flood	43	0	1	5	1	0	0	1
Irrigation method: other or not reported	10	0	0	1	1	1	4	1
Irrigation rate (ML per ha)	87	60	116	619	170	62	101	162
Irrigation rate (ML per t)	60	14	22	30	25	15	19	20
Crop thinning: preveraison	27	6	0	1	4	3	7	3
Crop thinning: veraison	41	24	8	0	13	3	7	9
Crop thinning: potveraison	59	0	1	0	2	0	15	3
Crop thinning: multiple times	18	13	5	0	0	3	5	5
At least one irrigation sensor	57	15	52	56	51	38	41	42
Regulated deficit irrigation	58	12	40	28	64	34	35	36
Partial rootzone drying	53	0	0	8	0	0	0	1
Leaching irrigation	62	0	6	28	27	2	4	10
Precision viticulture: multi-spectral imaging	26	3	6	9	21	10	12	10
Precision viticulture: soil mapping	38	0	5	5	2	12	5	5
Nutrition: tissue analysis	43	27	44	45	56	44	52	45
Nutrition: soil analysis	40	27	38	32	42	53	59	43
Macronutrient application: N	60	45	60	88	76	55	65	64
Macronutrient application: P	41	51	47	56	73	61	62	58
Macronutrient application: K	78	37	44	54	53	71	71	55
Macronutrient application: Mg	66	17	17	58	58	56	56	42
Macronutrient application: S	53	6	18	39	29	34	33	26
Macronutrient application: Ca	68	17	23	57	36	48	51	37
Micronutrient application: Fe	73	11	14	31	29	14	41	23
Micronutrient application: Mn	62	11	32	56	47	21	43	34
Micronutrient application: Zn	79	9	28	62	55	51	58	42
Micronutrient application: B	59	35	29	42	23	57	59	40
Micronutrient application: Cu	42	12	15	29	29	22	31	22
Micronutrient application: Mo	53	9	10	20	43	34	38	25
Micronutrient application: Al	39	3	1	2	4	2	10	4
Undervine strip management: herbicide	34	65	88	89	93	89	92	86
Undervine strip management: cultivation	35	6	3	2	4	2	1	3
Undervine strip management: slashing	28	28	8	9	3	7	6	10
Undervine strip management: other	7	1	1	0	0	2	1	1
Undervine strip mulch added	40	34	31	15	39	27	37	32

Mid-row management: herbicide	22	7	6	21	0	8	3	7
Mid-row management: cultivation	52	13	6	20	1	4	2	7
Mid-row management: cover crops	53	77	85	53	99	84	95	84
Mid-row management: other	19	3	4	6	0	4	0	3
Management of grown cover-crops/swards: slashing/mowing	39	100	98	92	100	95	97	97
Management of grown cover-crops/swards: knockdown herbicide	47	0	12	29	4	0	1	7
Management of grown cover-crops/swards: rolling	45	0	2	2	5	0	0	2
Management of grown cover-crops/swards: cultivation	40	7	6	23	0	0	0	5
Management of grown cover-crops/swards: livestock grazing	43	21	31	8	60	51	36	36
Certified organic	34	1	1	6	1	1	8	3
Certified biodynamic and organic	16	2	6	0	0	2	1	2
In 3-year transition to certified organic	29	0	1	1	3	1	0	1
Red: machine-harvested	84	6	84	100	92	89	61	71
Red: hand-picked	84	94	16	0	8	11	39	29
White: machine-harvested	76	18	85	100	70	86	66	70
White: hand-picked	76	82	15	0	30	14	34	30
Red: on-harvester destemming	50	0	3	0	13	1	29	9
White: on-harvester destemming	29	0	3	0	5	5	24	7
Side-arm discharge	62	50	95	100	88	93	51	79
On-harvester bins	61	0	5	0	12	7	49	14
Red: SO2 addition	79	0	86	88	95	93	67	72
White: SO2 addition	56	15	79	88	54	97	80	69

Notes: Explained is the percentage of the variance explained by the first four principal components of the PCA. The groups of regions are described in Table 3. The average values for each group of regions and all the regions combined are percentages unless otherwise stated in brackets after the name of each variable. Estimated with data from Nordestgaard (2019).