Supplementary material to:

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Appendix 1. Annual rainfall (mm) for South Africa's nine provinces: 1970–2006.

	Western Cape	Eastern Cape	Northern Cape	Free State	KwaZulu-Natal	North West	Gauteng	Mpumalanga	Limpopo	South Africa
1970	455	621	203	466	774	405	569	609	421	502
1971	481	697	257	539	1010	631	893	912	639	673
1972	433	538	230	534	911	528	607	893	730	600
1973	416	561	290	502	946	591	686	966	655	624
1974	638	914	583	792	955	713	732	879	733	771
1975	528	635	364	675	1033	764	930	965	748	738
1976	683	904	481	806	1198	852	850	907	755	826
1977	751	684	329	573	977	623	716	862	829	705
1978	443	644	206	619	1108	591	800	890	777	675
1979	500	623	213	572	750	531	679	716	538	569
1980	530	470	217	484	759	520	731	866	762	593
1981	715	739	307	683	919	585	644	828	754	686
1982	524	517	213	498	721	470	568	556	395	496
1983	612	546	218	531	843	428	726	830	469	578
1984	565	519	179	466	1149	340	487	866	560	570
1985	676	816	283	521	1053	404	678	832	661	658
1986	603	647	184	585	836	519	713	742	540	597
1987	592	589	217	670	1334	477	830	945	622	697
1988	488	785	443	879	1121	714	627	809	678	727
1989	639	752	265	624	1024	630	786	866	602	687
1990	553	528	227	463	832	433	604	762	522	547
1991	583	662	373	687	1001	590	723	814	598	670
1992	613	451	123	380	550	337	507	566	429	440
1993	637	675	231	587	872	495	757	797	571	625
1994	533	597	208	446	763	387	691	585	396	512
1995	623	665	274	639	1042	612	876	832	647	690
1996	711	733	301	761	1103	647	959	1097	958	808
1997	510	665	232	636	1167	685	962	895	700	717
1998	563	697	215	638	878	594	719	848	631	643
1999	403	386	245	378	892	420	526	798	650	522
2000	498	763	289	671	1160	629	1006	1233	1274	836
2001	603	696	342	744	905	624	646	770	738	674
2002	608	663	251	566	794	431	569	620	367	541
2003	491	481	146	413	637	407	506	517	419	446
2004	537	689	205	516	865	534	690	828	731	622
2005	507	578	205	532	766	468	535	631	428	517
2006	624	879	351	771	1032	730	771	964	796	769
Average	**564**	**649**	**267**	**590**	**937**	**550**	**711**	**819**	**641**	**637**

Source: South African Weather Bureau.

Appendix 2. Average daily maximum temperature (°C) for South Africa's nine provinces: 1970–2006.

	Western Cape	Eastern Cape	Northern Cape	Free State	KwaZulu-Natal	North West	Gauteng	Mpumalanga	Limpopo	South Africa
1970	24.2	23.5	25.6	25.2	24.00	27.1	24.2	25.5	27.4	25.2
1971	24.1	23.0	25.5	24.6	23.37	25.7	23.0	24.2	26.2	24.4
1972	25.3	23.7	26.4	24.8	23.80	26.4	23.6	24.3	26.3	25.0
1973	25.2	24.0	26.0	24.7	23.43	26.3	23.4	24.6	26.2	24.9
1974	24.6	23.5	25.0	23.3	23.87	25.2	22.6	24.3	25.9	24.2
1975	25.0	23.5	25.4	24.1	23.46	25.6	22.9	24.3	26.0	24.5
1976	24.4	23.6	24.8	23.2	23.69	25.1	22.4	24.2	25.8	24.1
1977	24.7	24.0	25.5	24.7	24.42	26.5	23.8	25.0	26.6	25.0
1978	24.9	23.4	25.7	24.4	23.60	26.2	23.4	24.7	26.4	24.8
1979	25.0	23.5	26.0	24.7	23.66	26.6	23.9	24.6	26.3	24.9
1980	25.2	24.1	26.2	24.6	24.09	26.2	23.4	24.4	25.9	24.9
1981	24.7	23.4	25.2	23.4	23.55	25.6	23.0	24.0	25.6	24.3
1982	24.7	23.5	25.9	24.9	24.02	27.0	24.2	25.1	26.8	25.1
1983	24.8	24.2	25.9	25.6	24.30	27.6	24.6	25.4	27.4	25.5
1984	25.3	24.1	26.4	25.2	23.71	27.4	24.2	24.3	26.6	25.3
1985	25.2	24.4	26.2	25.2	24.66	27.3	24.4	25.0	26.5	25.4
1986	25.1	24.0	25.9	25.1	24.25	27.1	24.1	24.7	26.8	25.2
1987	24.9	24.0	25.9	25.1	23.94	27.4	24.2	24.9	27.0	25.3
1988	24.9	23.6	25.4	24.0	23.89	26.4	23.7	24.8	26.0	24.7
1989	24.7	23.3	25.1	24.1	23.79	26.3	23.5	24.7	26.5	24.7
1990	24.4	23.5	25.4	25.2	23.44	27.2	24.0	24.8	26.9	25.0
1991	24.6	24.0	25.4	24.5	24.08	26.5	24.0	25.1	26.9	25.0
1992	24.6	24.3	25.9	26.3	25.06	28.2	25.4	25.9	28.3	26.0
1993	25.4	24.3	26.1	24.8	24.58	27.0	24.3	24.9	27.3	25.4
1994	25.2	24.1	26.1	24.5	24.13	26.7	23.8	24.3	27.1	25.1
1995	24.5	23.6	25.6	24.8	23.67	26.7	24.2	24.1	27.3	25.0
1996	23.7	23.4	24.3	23.8	23.31	25.8	23.3	23.3	26.3	24.1
1997	24.8	23.5	25.7	24.7	23.23	26.2	23.5	23.8	26.8	24.7
1998	25.0	24.1	26.3	25.2	24.19	27.4	24.8	24.8	27.7	25.5
1999	25.7	25.0	26.3	25.7	25.08	27.3	24.5	24.2	27.3	25.7
2000	24.8	23.5	25.8	24.1	23.73	25.7	23.2	23.5	26.1	24.5
2001	24.6	24.1	25.6	24.2	24.31	26.2	24.2	24.0	26.8	24.9
2002	25.0	24.2	25.8	25.2	24.23	27.1	24.4	24.2	27.8	25.3
2003	25.0	24.5	25.9	25.9	24.33	27.6	25.1	24.3	28.2	25.6
2004	25.7	24.8	26.5	24.7	24.46	26.6	23.8	24.1	27.1	25.3
2005	25.1	24.5	26.0	25.4	24.46	27.3	25.1	24.3	28.3	25.6
2006	25.3	23.9	26.2	22.7	24.35	25.5	23.9	23.5	26.9	24.7
	24.9	**23.9**	**25.8**	**24.7**	**24.0**	**26.6**	**23.9**	**24.5**	**26.8**	**25.0**

Source: South African Weather Bureau.

Appendix 3. Explaining the SUR mode.

We employed the SUR model with a one-way error component, which allows cross-section heterogeneity in the error term; i.e. $u_{it} = \mu_i + \nu_{it}$. On the other hand, a two-way error component model allows cross-section heterogeneity, as well as time effects; i.e. $u_{it} = \mu_i + \lambda_t + \nu_{it}$. We adopt Avery's[21] approach, as presented in Baltagi,[16] to explain a SUR model in a panel context. The SUR model has a set of M equations:

$$y_j = Z_j\delta_j + \mu_j \text{ with } \mu_j = Z_\mu \mu_j + \nu_j \quad j = 1,...M\,, \tag{1}$$

where y_j is $NT \times 1$; Z_j is $NT \times k_j^{`}$ and the residuals from each equation with random vectors of $Z_u = (I_n \otimes l_T)$; $\mu_j' = (\mu_{1j},...\mu_{Nj})$ and $\nu_j' = (\nu_{11j},.....,\nu_{1Tj},....,\nu_{N1j},...,\nu_{NTj})$.

In addition, $\mu \sim (0, \Sigma_\mu \otimes I_N)$ and $\nu \sim (0, \Sigma_\nu \otimes I_{NT})$. From Equation 1, it follows that each different equation has the same standard variance-covariance matrix. However, within a panel SUR model, there are additional cross-equation variance components. Accordingly, Avery[21] defined a variance-covariance matrix that is not equation specific:

$$\Omega = E(\mu\mu^{`}) = \Sigma_\mu \otimes (I_N \otimes J_T) + \Sigma_\nu \otimes (I_N \otimes I_T)\,, \tag{2}$$

where $\mu' = (\mu_1',....,\mu_M')$ is a $1 \times MTN$ vector of disturbances with μ_j and $\Sigma_u = [\sigma^2_{ujt}]$, as well as, $\Sigma_\nu = [\sigma^2_{\nu jt}]$ are both $M \times M$ matrices. Replacing J_T with $T\bar{J}_T$ and I_T by $E_T + \bar{J}_T$ provides the following:

$$\Omega = (T\Sigma_\mu + \Sigma_\nu) \otimes (I_N \otimes \bar{J}_T) + \Sigma_\nu \otimes [(I_{NT} - I_N \otimes \bar{J}_T)]\,. \tag{3}$$

It is then possible to estimate Equation 3 in a panel context, by replacing the matrix of disturbances for all M equations by OLS (Ordinary Least Squares) residuals[21] or within-type residuals.[16] To quantify the impact of rainfall's contribution to agriculture, we used an econometric model custom-made for this purpose. A net income function was estimated and fitted to the data with a cross-section SUR model for field crops, horticulture and animal production, respectively.

$$Y_i^* = f(input_i, wages_i, con_i, prod_i, temp_i, rain_i)\,, \tag{4}$$

where Y_i = net income for province i; Input$_i$ = expenditure on intermediary goods and services for province i; Wages$_i$ = wages, interest, and other sundry expenses for province i; Con$_i$ = proportional contribution to GDP for province i; Prod$_i$ = an index of gross income for province i; Temp$_i$ = temperature for province i; Rain$_i$ = rainfall for province i.

We compiled three separate models for each agricultural product, namely FC (field crops), H (horticulture), and AP (animal production), respectively, where each model contained the above independent variables per region/province and the dependent variable, i.e. the net income per province, for the respective agricultural product. After the initial round of estimating the net income function—for FC, H, or AP respectively—for each of the nine provinces, using the one-way error SUR model, two problems were encountered—heteroscedasticity and serial correlation—both of which had to be corrected, as we will now explain.

Heteroscedasticity

The standard SUR one-way error component model assumes that the regression disturbances are homoscedastic, when the same variance across time and individuals occurs. This may be a restrictive assumption for panels and agricultural type data, where the cross-sectional units may be varying in size and, as a result, may exhibit different variations.[22] Therefore, to correct for the potential problem of heteroscedasticity, White's cross-section heteroscedastic structure was specified in all the models, to ensure consistency and efficiency of the estimators.

Serial correlation

Another problem within the standard SUR one-way error component model is the assumption that the only correlation over time is due to the presence of the same individual effect across the panel.[22] This assumption ignores the effect of an unobserved shock that took place in the current period on the following periods, causing inefficient estimates of regression coefficients and biased standard errors. In an attempt to test for serial correlation, we employed the Durbin-Watson (DW) test and Lagrange Multiplier (LM) test. In particular, the LM-test is based on the test for random effects and serial correlation, where the null hypothesis is $H_0 = \sigma^2_\mu = 0; \lambda = 0$ or $H_0 = \sigma^2_\mu = 0; \rho = 0$. To construct the test, the following specification was used:

$$LM_1 = \frac{NT^2}{2(T-1)(T-2)}[A^2 - 4AB + 2TB^2] \overset{H_0}{\sim} \chi^2_2\,, \tag{5}$$

where $A = [\hat{u}'(I_N \otimes J_T)\hat{u}/(\hat{u}'\hat{u}) - 1]$ $(\sigma^2_\mu = 0)$; $B = A = (\hat{u}'\hat{u}_{-1}/(\hat{u}'\hat{u})$ $(\rho = 0)$ and $\hat{u}$ is OLS residuals.

The null hypothesis is rejected if the LM statistic exceeds the $\chi^2_2 (= 5.99)$ value. Moreover, Bhargava *et al.*[22] outlined the DW-test, with the null and alternative hypotheses as H_0: $\rho = 0$ and $H_A : |\rho| < 1$. These authors defined the test statistic as:

$$d_p = \sum_{i=1}^{N}\sum_{t=2}^{T}(\tilde{\nu}_{it} - \tilde{\nu}_{i,t-1})^2 \Big/ \sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{\nu}^2_{it}\,, \tag{6}$$

with ν_{it} is the within residuals.

The critical values in Table II from Bhargava *et al.*[22] form the decision basis for this test. With the application of the DW and LM-tests, the results in Table A3.1 indicate that serial correlation was present.

Table A3.1. Results showing the presence of serial correlation.

Test	Field crops	Horticulture	Animal production
DW*	3.09	3.05	3.24
LM	69.35	50.27	50.73

*The DW-statistics show that negative serial correlation is present.

To correct for serial correlation, we estimate rho-values for each model and each province to account for the heterogeneity across the provinces. The rho-values reported in Table A3.2 confirm the presence of serial correlation in both models along with heterogeneity across the regions.

Table A3.2. Estimated rho-values as per region.

Province	Estimated rho-value		
	Field crops	Horticulture	Animal production
Western Cape	0.76	0.53	0.72
Eastern Cape	0.79	0.63	0.63
Northern Cape	0.78	0.89	0.79
Free State	0.67	0.81	0.78
Natal	0.79	0.93	0.69
North West	0.83	0.84	0.71
Mpumalanga	0.91	0.85	0.47
Gauteng	0.63	0.85	0.71
Limpopo	0.76	0.54	0.74

To correct for the serial correlation problem, the rho-values shown in Table A3.2 are used to transform the correlated errors into uncorrelated errors, based on a Prais-Winston transformation approach for each province. The DW- and LM-tests are performed again to determine whether serial correlation is still present in the models. Table A3.3 shows that the serial correlation problem has been addressed.

It is important to note that, with the correction for serial correlation, the sample size changed from the period 1971 to 2006, since observations have been lost through differentiation in the data transformation process. Given that the major data problems have been rectified, the final SUR models can now be presented. The results of each model are shown separately, first the field crops model, then the animal production model, and, last, the horticulture model.

Table A3.3. Results showing no serial correlation.

Test	Field crops	Horticulture	Animal production
DW*	2.21	2.16	2.26
LM**	5.69	5.54	5.59

*Constructing the critical value utilizing Table II from Bhargava *et al.*[22] with $T \approx 10$, $H \approx 250$ and $N \approx 9$. Following this approximation, the critical values yield 1.927 (D_{pL}) and 1.942 (D_{pU}).