Econometric Analysis of Global Climate Change

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Abstract This paper reports on our research on applying econometric time series methods to the analysis of global climate change. The aim of this research has been to test hypotheses about the causes of the observed historical rise in global temperatures. Longer term applications include policy analysis and use of the model as a module in integrated assessment. Research to date has comprised three phases. In the first (published) phase we used the concept of Granger causality and differences between the temperature record in the northern and southern hemispheres to investigate the causes of temperature increase. In the second phase we use a single equation cointegration analysis of first order integrated variables to examine the causes of global temperature change. Both these analyses indicate that increases in greenhouse gases and solar irradiance, modulated by sulphate aerosol concentrations, are responsible for the observed changes in temperature. In the third, current, stage of research we are examining the possibilities of modelling climate change as a second-order cointegrated system. This approach may be able to address anomalies raised by our earlier research.

1. INTRODUCTION

It has been argued that "Empirical studies of relationships between smoothed forcing factors and the statistically non-stationary historical temperature record cannot, alone, resolve the relative contributions of the different forcing factors .... rigorous statistical tools do not exist to show whether relationships between statistically non-stationary data of this kind are truly statistically significant" (Folland *et al.*, 1992, p163). This is no longer true. The inability to detect relations among nonstationary variables also presented considerable problems for macroeconomists. Vector autoregression (Sims, 1980) and cointegration techniques were developed (Engle and Granger, 1987; Johansen, 1988) to detect and quantify relations among macroeconomic variables such as GDP and aggregate price levels that are non-stationary trending variables that may have possibly common long run trends. Cointegration analysis has a similar aim to spectral analysis but looks for common stochastic trends in nonstationary variables rather than common cycles in stationary variables and estimation is generally carried out in the time domain rather than the frequency domain.

This paper reports on our research on applying econometric time series methods to the analysis of global climate change. Very few researchers have previously used time domain econometrics methods in this context. Apart from ourselves (Kaufmann and Stern, 1997; Stern and Kaufmann, 1997) only Tol and de Vos (1993) and Tol (1994) have explicitly argued that they use econometric time series methods in investigating the causes of climate change, though Schönwiese (1994) uses an econometric type model with lagged independent variables. We have, however, used a consistent methodology and techniques developed in econometrics in the last couple of decades which have not previously been applied to this problem. Other statistical studies have applied frequency domain methods (e.g. Kuo et al., 1990; Thomson, 1995) and simple regression models (e.g. Lean et al., 1995).

Our research to date has proceeded through three stages. Initially we used a simple vector autoregression model to analyse causes of changes in northern and southern hemisphere temperatures (Kaufmann and Stern, 1997). In the second, completed (but so far unpublished), phase we examined the time series properties of global change variables and estimated a small cointegration model (Stern and Kaufmann, 1997). In the third, current, phase we are employing various approaches aimed at clearing up anomalies raised by the first two phases of research and paving the way for a more complete and sophisticated model.

Most of our research to date has tested hypotheses about the causes of climate change and to a lesser degree quantified the contributions of various forcing factors to the observed change in global temperature. In subsequent phases we aim to concentrate more on quantifying these relative contributions and proceeding to develop a small econometric model of climate change that could be used as a module in integrated assessment exercises.

2. GRANGER CAUSALITY AND HEMISPHERIC TEMPERATURE RELATIONS

The first phase of our research exploits the differences between the northern and southern hemispheres in terms of anthropogenic variables and their possible effects on climate. While greenhouse gases such as carbon dioxide, CFCs, nitrous oxide, and, to a lesser degree, methane are relatively well mixed between the hemispheres, sulphate aerosols that reduce radiative forcing are short-lived and have their major effect fairly close to the source region. Most of the tropospheric sulphate aerosol is emitted from northern hemisphere economies. Therefore if the build-up of greenhouse gases in the atmosphere has already increased temperatures the signal should be more apparent in southern hemisphere temperatures which would be less "contaminated" by the "noise" due to sulphate aerosols.

The main tool we use is the Granger causality test (Granger, 1969). Granger causality tests are based on the notion of predictability. If past values of X improve forecasts of Y given all relevant past information on Y including its own lagged values, X Granger causes Y. This implies that Y is the dependent variable and X an independent variable. The test is carried out by jointly restricting the coefficients of the lagged values of X to zero in the equation explaining Y in a vector autoregression (VAR) model. A VAR model can be represented by:

$$y_t = A_1 y_{t-1} + \ldots + A_k y_{t-k} + \mu + \delta t + \varepsilon_t$$

where y is a vector of variables, the A_i are matrices of regression coefficients and ε is a vector of white noise processes.

The detection of Granger causality does not necessarily imply the presence of a physical causal mechanism between the two variables. Furthermore, the detection of Granger causality depends on the information set of conditioning variables. The coefficient estimates may be biased by the omission of relevant variables that are in fact the causal variables.

Specifically, we test whether southern hemisphere temperatures Granger cause northern hemisphere temperatures and vice versa in the presence of different sets of conditioning variables. We use the temperature series developed by Jones et al. (1994) for the period 1865-1994.

The results in Table 1 show that there is south to north causality in simple models which include no conditioning variables or only changes in solar irradiance (Lean et al., 1995), stratospheric sulphates (Sato et al., 1993), and tropospheric sulphates. However, when greenhouse gas concentrations are introduced into the model the Granger causality disappears. All these variables are transformed to reflect their contribution to radiative forcing (Kattenberg *et al.*, 1996). A number of sensitivity tests and other investigations indicate the robustness of this result (Kaufmann and Stern, 1997).

We interpret this result to indicate that southern hemisphere temperatures act as a proxy variable for the greenhouse gases (and changes in solar irradiance). They therefore explain changes in the northern hemisphere which are also partly driven by the increase in greenhouse gases. However, sulphate aerosols have a strong effect on northern hemisphere temperatures but not on southern hemisphere temperatures. Therefore, northern hemisphere temperatures are not useful in predicting southern hemisphere temperatures. This interpretation is supported by cointegration modelling currently in progress.

Table 1 Significance Levels of Granger Causality Tests

Model 1 (Temperature Only)	
North Causes South	0.79
South Causes North	0.016
Model 2 (Model 1 +Natural Variables)	
North Causes South	0.57
South Causes North	0.013
Model 3 (Model 2 + Greenhouse Gases)	
North Causes South	0.90
South Causes North	0.081
Model 4 (Model 2 + Tropospheric Sulphates)	
North Causes South	0.70
South Causes North	0.010
Model 5 (Model 2 + GG's + TS's)	
North Causes South	0.83
South Causes North	0.12

The south to north causal order appears to have strengthened over time - another possible sign of an anthropogenic cause. Figure 1 shows the significance level of the south-north Granger causality test as the sample period is incrementally increased by one year.

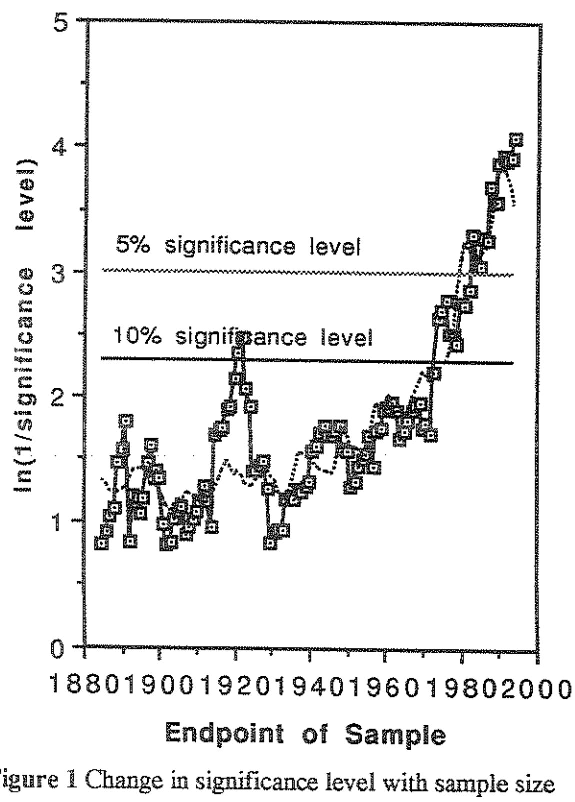

Figure 1 Change in significance level with sample size

Tests show that this is not simply due to the larger sample. The recent data is more informative and it seems that this can be explained by changes in the forcing variables (Kaufmann and Stern, 1997).

To further test our methodology we applied the Granger causality test to the output from the Hadley Centre GCM (Mitchell *et al.*, 1995). We found south to north Granger causality in the output from a simulation of the historic atmosphere but not in control simulations or in forecasts of future conditions (when sulphur emissions shift southward).

3. A MORE DIRECT APPROACH

In this phase of our research we investigate the time series properties of a group of global change variables and estimate a simple cointegration model for global temperature. This cointegration approach is a more direct test of the effect of radiative forcing variables on temperature than the approach we used in the first phase.

Classical regression models assume that the variables are stationary i.e. that two sub samples of the sample used have the same distribution. One possible way for a variable to be nonstationary is for it to contain a stochastic trend or unit root process. For example, in the case of a first order autoregressive process (AR(1)) if the autoregressive coefficient is unity then the process becomes a random walk i.e. it has a stochastic trend.

$$z_t = \alpha z_{t-1} + \beta t + \mu + \varepsilon_t$$

ε_t is a white noise process and t is a deterministic time trend. If $\alpha = 1$ then $z_t \sim I(1)$ - it is integrated of order one i.e. it is a random walk. If $\alpha < 1$ then $z_t \sim I(0)$ - it is integrated of order zero. If in the latter case $\beta = 0$ the process is said to be levels stationary, while if $\beta > 0$ it is said to be trend stationary.

Table 2 Tests for Stochastic Trends

Variable	Dickey-Fuller	Phillips-Perron	Schmidt-Phillips
Temp - nhem	I(1)	I(0)	I(0)
Temp - shem	I(0)	I(0)	I(0)
Temp - global	I(1)	I(0)	I(0)
CO_2	I(2)	I(1)	I(1)
CH_4	I(1)	I(1)	I(1)
CFC11	I(2)	I(2)	I(2)
CFC12	I(2)	I(2)	I(2)
N_2O	I(1) to I(2)	I(1)	I(1)
Sun	I(1)	I(1)	I(1)
Stratospheric Sulphates	I(0)	I(0)	I(0)
SOx emissions	I(1)	I(1)	I(1)

Standard econometric tests can be used to detect the presence of a stochastic trend. The most prominent of these originated with Dickey and Fuller (1979), Phillips and Perron (1988), and Schmidt and Phillips (1992). We applied these tests to a number of important global change variables. The results are summarised in Table 2. I(2) indicates a second order integrated process. This term is explained in the next section. Stochastic trends are found to be present or possibly present in most of the variables except the stratospheric sulphate series. The temperature series are borderline. Some tests indicate stochastic trends while others do not.

Most linear combinations of I(1) variables are also I(1). Regressions of such variables will not produce consistent parameter estimates. However, a linear combination of integrated variables may be stationary if they share one or more common stochastic trends. In the latter case, the variables are said to cointegrate (Engle and Granger, 1987). A simple example is shown in the following two equations:

$$C_t = \alpha + \gamma E_t + e_t$$
$$E_t = E_{t-1} + \beta + \eta_t$$

where e is a stationary but not necessarily white noise process and η_t is a white noise process. In the absence of forcing by the random walk E, C would be a stationary variable. In this case a regression of C_t on E_t will have stationary residuals and consistent parameter estimates. The regression acts to "zero out" the integrated variable E_t. The cointegrating vector is said to be $[1\ -\alpha\ -\gamma]$ so that the stationary linear combination $[C_t - \alpha - \gamma E_t]$ represents a long-run equilibrium relationship.

The Granger Representation Theorem (1987) states that if y_t cointegrates then it has a vector error correction model (VECM) representation:

$$\Delta y_t = \Pi_1 \Delta y_{t-1} + ... + \Pi_{k-1} \Delta y_{t-+1k} + \alpha\beta' y_{t-1} + \mu + \delta t + \varepsilon_t$$

where α is the adjustment coefficient(s) and β is the cointegrating vector(s). This is a reparameterisation of the VAR model above. Both the number of cointegrating vectors and the parameters can be estimated by maximum likelihood using the procedure developed by Johansen (1988).

We applied the Johansen method to estimate a single equation autoregressive model for global temperature (Jones *et al.*, 1994). The estimates of α and β are presented in Table 2. Other parameter estimates are given in Stern and Kaufmann (1997).

Table 3 Cointegration Model

	Coefficient	Standard error
Cointegrating vector β - Long run relation		
Temperature	1.000	0
Trace gases	-0.458	.089
Solar irradiance	-0.458	.089
Tropospheric sulphates	-1.448	.369
Time trend	-0.008	.002
Loading factor α- Adjustment to long run relation		
	-0.590	0.093

All the estimated parameters are significant. We also tested whether temperature could be represented by a trend stationary process. The null hypothesis was strongly rejected. Temperature has, therefore, a stochastic trend and there is cointegration between temperature and the radiative forcing variables. The cointegration model apparently helps reveal this trend by reducing the noise in the temperature series (c.f. Hansen, 1993).

The negative signs on the coefficients of the radiative forcing variables indicate that they have a positive effect on temperature. The climate sensitivity (long-run temperature impact of doubling CO_2) is estimated to be 2.0°C.

4. SOLVING THE PUZZLES

There are a number of outstanding problems with the results obtained so far:

1. In the cointegration model the time trend is much too large (+0.08°C per decade in the absence of greenhouse warming). The adjustment rate of temperature to long-run equilibrium (59% per annum) is much too fast.

2. We have not been able to estimate reasonable equations for CO_2 and CH_4. Climate feedbacks are likely to be important but are ignored in the models estimated so far. Also translating emissions into temperature impacts as required in integrated assessment requires the modelling of these gases.

3. Various other sources of evidence (including Table 2) show that some I(2) behaviour occurs and that an I(1) cointegration model may be inappropriate.

The following equations are a simple example of an I(2) stochastic process:

$$z_t = z_{t-1} + \mu_{t-1} + \varepsilon_t$$

$$\mu_t = \mu_{t-1} + \eta_t$$

where ε_t and η_t are both white noise processes. In this example μ_t is a random walk (I(1)) and z_t is a random walk forced by another random walk (I(2)). An I(2) cointegrated system can allow more complex dynamics and slower returns to equilibrium than are accommodated by I(1) cointegration models.

The problems in 1. are we believe partly due to forcing the model into a single global equation and also due to assuming that all variables are I(1).

As a first step we are currently estimating a cointegration version of the model developed in the first phase with separate equations for northern and southern hemisphere temperatures. Results are similar to the Granger causality results reported above and parameter estimates are improved relative to those in Table 3. The time trend is insignificant and sulphates have a coefficient closer to those of the trace gases. However, the adjustment coefficient is still much larger than expected. Preliminary I(2) cointegration models that we have estimated show that dropping the I(1) assumption leads to much lower estimates of the adjustment coefficient. It also may allow estimation of reasonable equations for CO_2 and CH_4.

There is one problem with the interpretation that the system is an I(2) cointegrated system. While the evidence that, for example, CO_2 concentrations are I(2) is pretty good there is no firm evidence in the above that temperature is an I(2) process. The standard unit root tests have difficulty in determining that temperature is integrated at all. A physically meaningful model in which CO2 drove temperature would imply that at least in the southern hemisphere temperature was an I(2) process. In the northern hemisphere it is possible that there is cointegration between sulphate aerosols (if they are also I(2) and trace gases so that the net radiative forcing is I(1). Some results from preliminary I(2) cointegration models suggest that temperature could be a noisy I(2) process but these are not very clear cut as yet.

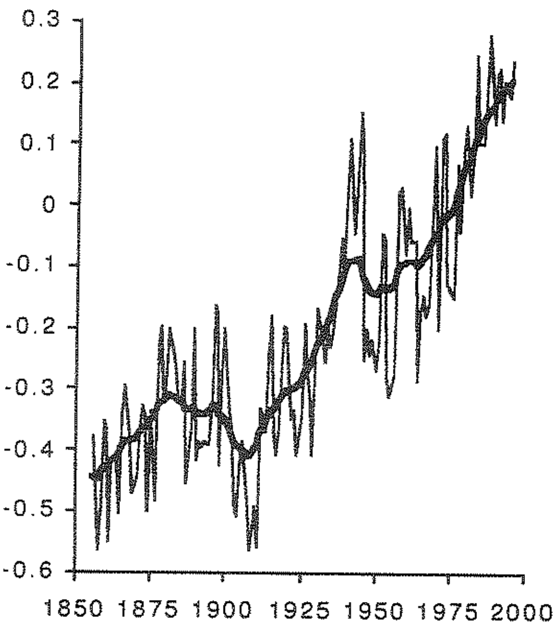

Figure 2 Southern hemisphere temperatures and fitted stochastic trend

As an alternative we propose to use signal extraction methods to model the stochastic trend present in the temperature series. In this approach a structural time series ARIMA (p, 2, q) model is fitted to the series using the Kalman filter to evaluate the likelihood function and predict the stochastic trend (see Harvey, 1989):

$$T_t = \mu_t + e_t$$

$$\mu_{t+1} = \mu_t + \lambda_t + \eta_t$$

$$\lambda_{t+1} = \lambda_t + \upsilon_t$$

where T_t is the temperature series, e_t is a stationary ARMA process and η_t and υ_t are white noise errors with uncorrelated variances $\sigma^2(\eta_t)$ and $\sigma^2(\upsilon_t)$. A test of the null hypothesis $\sigma^2(\upsilon_t) = 0$ is a test of the hypothesis that $T_t \sim I(1)$ as opposed to the alternative that $T_t \sim I(2)$

Initial results are promising. Figure 2 presents a trend fitted to the southern hemisphere temperature series. We have not yet determined whether this is the maximum likelihood estimate. The trend shown is I(2) and shows some similarity to the stochastic trends in carbon dioxide and other trace gases. Preliminary tests show that it may cointegrate with these gases to an I(1) disequilibrium.

5. CONCLUDING COMMENTS

So far we have gained a number of important insights from our research. First, we have shown that econometric methods are useful in the study of climate change when applied rigorously and consistently. Somewhat surprisingly, the available data do appear adequate for the purpose. However, we have learned that the time series properties of the data are quite complex and may require the use of I(2) cointegration modelling as opposed to the simpler I(1) approach. We have also learned that it is necessary and useful to treat the two hemispheres separately. On the substantive side our research appears to indicate that people have already altered the climate and possibly that this signal is strengthening. Other variables such as changes in solar irradiance may also play a role in the observed warming.

However, we are still some way from achieving all the goals of our research which include quantifying the contributions of different variables to historic climate change and developing a structural model that could be used for integrated assessment. Development of an I(2) cointegration model will hopefully aid in the achievement of these aims.

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