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IS THERE A GLOBAL WARMING SIGNAL IN HEMISPHERIC TEMPERATURE SERIES?

by

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Abstract

Global and hemispheric temperatures, greenhouse gas concentrations, solar irradiance, and anthropogenic sulfate aerosols all have increased during the last one hundred and fifty years. Classical linear regression techniques will indicate a positive relationship among such series whether or not such a relation exists. Such standard techniques cannot, therefore, show whether observed temperature increases are the result of anthropogenic climate change. However, recent developments in econometrics allow for the analysis of relationships between statistically non-stationary data. We apply some of these recently developed tests in order to uncover the presence of stochastic trends in global climate change variables. These tests indicate that the greenhouse gases are characterized by I(2) stochastic trends while they fail to find evidence of an I(2) stochastic trend in hemispheric temperature series. This would mean that there is no simple long-run equilibrium relationship between radiative forcing and temperature. We then use a multivariate structural time series model to decompose Northern and Southern Hemisphere temperatures into stochastic trends and autoregressive noise processes. This method does not suffer from some of the disadvantages of the standard tests. The results show that there are two independent stochastic trends. The first is I(2) and is shared by the Northern and Southern Hemisphere temperatures. It may be related to the to the radiative forcing variables and represent a global warming signal. The second trend is I(1) and is only present in Northern Hemisphere temperatures. This trend seems closely related to the radiative forcing due to tropospheric sulfates.

1. Introduction

Global and hemispheric temperatures, greenhouse gas concentrations, solar irradiance, and anthropogenic sulfate aerosols all have increased during the last one hundred and fifty years. Classical linear regression techniques will indicate a positive relationship among such series whether or not such a relation exists. Such standard techniques cannot, therefore, show whether observed temperature increases are the result of anthropogenic climate change. Further, it has been argued that "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). However, recent developments in econometrics allow for the analysis of relationships between statistically non-stationary data. Cointegration techniques (Engle and Granger, 1987; Johansen, 1988) are used by macro-economists to detect and quantify relations among variables such as GDP and aggregate price levels. These non-stationary trending variables may share common long-run stochastic trends. Cointegration analysis has a similar aim to spectral analysis, but it looks for common stochastic trends in nonstationary variables rather than common cycles in stationary variables and carries out estimation in the time domain rather than the frequency domain. Cointegration analysis can also be considered as a dynamic version of factor analysis.

The aim of this paper is to use these newly available statistically rigorous techniques to investigate whether hemispheric temperature series could show evidence of anthropogenic warming. The results show that Northern and Southern hemisphere temperatures share a common trend that may be due to anthropogenic warming, while the difference between the hemispheric temperature series may be related to the differential effects of anthropogenic sulfur emissions. While obviously not a novel conclusion substantively (e.g. Wigley, 1989), this study represents progress in the application of statistically rigorous methods to the question of anthropogenic climate change.

Few researchers have used time domain econometrics methods to analyze climate change. Apart from Kaufmann and Stern (1997), only Tol and de Vos (1993) and Tol (1994) explicitly use econometric time series methods to investigate the causes of climate change, though Schönwiese (1994) uses an econometric type model with lagged independent variables. Other statistical studies of climate change apply frequency domain methods (e.g. Kuo et al., 1990; Thomson, 1995) and simple regression models (e.g. Lean et al., 1995). No previous work has employed the notion of common stochastic trends or cointegration. Woodward and Gray (1993, 1995) have investigated whether global temperature contains a stochastic trend.

In this paper, we analyze temperature and radiative forcing data for the presence of stochastic trends in individual variables and for stochastic trends shared by two or more of these variables. In the second section we develop the notion of stochastic trends and use the presence (or absence) of stochastic trends to classify the time series properties of individual variables. These results cast doubt on the notion that temperature and radiative forcing variables share a stochastic trend, and hence that radiative forcing drives temperature. However, these tests have low power to reject the null hypothesis of the presence of a nonstationary stochastic trend in series that have a high signal to noise ratio and a tendency to reject the null in noisy series. The Kwiatowski, Phillips, Shin, and Schmidt (1992) test has a more conventional choice of null hypothesis i.e. the absence of a stochastic trend, but still suffers from similar problems. These tests are expected to be less useful on noisy series such as temperature than on series such as carbon dioxide concentrations. These problems are discussed in section 3.

In the second part of the analysis (sections 4. and 5.) we use the structural time series methodology promoted by Harvey (1989) to extract stochastic trend signals from hemispheric temperature series. These extracted trends are then statistically compared with relevant forcing variables. This approach provides a statistically rigorous method to extract nonstationary stochastic trends from temperature series and has several advantages over alternative methodologies. By optimally removing noise from the series to reveal the stochastic trend, instead of approximating the series by an autoregression and then testing various parameters in that model, the procedure avoids the problems of the conventional univariate tests. In addition, the null hypothesis is the absence of stochastic trends and the range of possible alternative hypotheses is greater than in other cointegration approaches.

The results show that the hemispheric temperature series share a stochastic trend that has properties similar to the stochastic trend in radiative forcing variables. The difference between the temperature series is a stochastic trend that may be related to radiative forcing associated with anthropogenic sulfur emissions.

2. Time Series Properties of Global Climate Variables

Time series can be characterized in many ways. We focus on the presence or absence of stochastic trends in the variables. The reason for this is that, unlike linear deterministic trends, stochastic trends provide a unique "fingerprint" for a variable which we can then look for in other series. A shared stochastic trend is taken as evidence for a causal relation between the series. In the following, we review the theory of stochastic trends and tests for stochastic trends, and apply those tests to a group of global climate change variables. We find evidence for the presence of stochastic trends. We also review the theory of cointegration and discuss its implications for the global climate variables.

a. Stochastic Trends

If a series is nonstationary but its first difference is stationary the series is said to be integrated of order one or I(1). A process that requires differencing twice to achieve stationarity is referred to as an I(2) process. A process that is stationary without differencing is referred to as an I(0) or "levels stationary" process. The trend in an integrated process once a stationary noise term is removed is known as a stochastic trend. For an I(1) process this trend is a simple random walk. An integrated variable shows no particular tendency to return to a mean or deterministic trend and shocks to the variable are "remembered" - they do not die out over time.

An I(2) process (which is the more general case) can be represented as follows:

$$y_t = A_t + \varepsilon_t \tag{1}$$

$$A_{t+1} = A_t + \gamma_t + \eta_t \tag{2}$$

$$\gamma_{t+1} = \gamma_t + \zeta_t \tag{3}$$

where ε_t, η_t, ζ_t are stationary (but possibly autocorrelated) processes with mean zero. In the general case, the stochastic trend A_t is known as a local linear trend process (Harvey, 1989), its slope γ_t is itself a random walk. If the variance of ζ_t is zero then y_t is an I(1) process as it is now a random walk with a deterministic drift equal to γ_0. If η_t also has zero variance then y_t has a deterministic trend. Though still non-stationary, this variable can be made stationary by the subtraction of a deterministic trend rather than by differencing. This type of I(0) process is known as a "trend stationary" process. If additionally $\gamma_0 = 0$, then y_t is stationary with mean A_0.

The representation of a stochastic process in (1) through (3) is used in the structural time series models used in sections 4. and 5. of this paper. An alternative representation of a stochastic process is used in a number of widely used tests for the presence of a stochastic trend reviewed and used in the next two subsections (2b., 2c.). This approach approximates the series by an autoregressive process. The advantage of this latter representation is that the model can be estimated using standard regression techniques, while the former representation must be estimated using Kalman filter techniques. The first order autoregressive representation is given by:

$$y_t = \mu + \beta t + \rho y_{t-1} + \varepsilon_t \tag{4}$$

where ε_t is a stationary random error process with mean zero, ρ is the autoregressive parameter, and t is a deterministic time trend. If $\rho = 1$ and $\beta = 0$ in (4) then y is a random walk with drift μ. The mean is non-constant over time and the process is nonstationary and integrated of order one.

Alternatively, if $\rho < 1$ then the series is either trend stationary if β 0 and levels stationary if $\beta = 0$. An I(2) process z_t can be modeled by (4) if $y_t =$ z_t i.e. the first difference of z_t.

b. Tests for Stochastic Trends

To test for the presence of stochastic trends, we use four tests. The Dickey-Fuller (Dickey and Fuller, 1979, 1981) and Phillips-Perron (Phillips and Perron, 1988) tests are the same but use different approaches to deal with serial correlation in the data. For both tests the null hypothesis is that the series contains a stochastic trend. The model for the Dickey Fuller test is:

$$\Delta y_t \quad = \quad \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \qquad (5)$$

where y is the variable under investigation and ε_t is a random error term. The number of lags p is chosen using the Akaike Information Criterion (Akaike, 1973). The lagged variables provide a correction for possible serial correlation. The null hypothesis is given by $\gamma = 0$. The alternative hypothesis is that the process is stationary around the deterministic trend. A further battery of tests looks at other alternatives including levels stationarity.

The Phillips-Perron test uses the same models as the Dickey-Fuller tests, but rather than using lagged variables, it employs a non-parametric correction (Newey and West, 1987) for serial correlation. We chose the lag truncation for this nonparametric correction using an automated bandwidth estimator employing the Bartlett kernel (Andrews, 1991). The test statistics for both the Dickey Fuller and Phillips Perron tests have the same distributions. Critical levels are reproduced in Hamilton (1994) and Enders (1995).

The model used in the Schmidt-Phillips test (Schmidt and Phillips, 1992) is given by equation (6):

$$\Delta y_t \quad = \quad \alpha + \gamma S_{t-1} + \varepsilon_t \qquad (6)$$

$$S_t \quad = \quad y_t - y_1 - \frac{t-1}{T} \sum_{t=1}^{T} \Delta y_t \qquad (7)$$

where T is the number of observations, and ε_t is a random error term. First the "residual" S_t is computed using equation (7) and then the regression in equation (6) is estimated. The test statistic is again a t-test on γ.[*] The null is again the presence of a stochastic trend, while the alternative is

[*] For all three tests the test statistic $\rho = T\gamma$ can also be used. The distributions for this test have been tabulated in the original papers and texts such as Hamilton (1994).

trend stationarity. Critical values for the test statistic are presented in Schmidt and Phillips (1992). We use the same correction for serial correlation as for the Phillips Perron test.

The Kwiatowski, Phillips, Schmidt, and Shin (1992) test (KPSS) differs from the other three tests in that the null hypothesis postulates that the series is stationary, the alternative is the presence of a stochastic trend. A second version has a null of trend stationarity. The test statistic is a Lagrange Multiplier statistic which is calculated as the square of the sum of residuals divided by the estimated error variance from a regression of the variable in question on either a constant or a constant and a trend. We again use the Andrews / Newey-West procedure to correct for serial correlation.

c. Results of Univariate Tests

We use the four tests described above to determine the presence of stochastic trends in a selected group of global climate change data (the Appendix describes sources for the data series) for the longest time series available (Table 1).[*] In general the KPSS test shows the highest order of integration and the Phillips-Perron and Schmidt-Phillips tests show the lowest. The KPSS test shows that all the temperature series are I(1), all the gas concentration series are I(2), solar irradiance and SOx emissions are I(1) and stratospheric sulfates are I(0). On the other hand the Phillips-Perron and Schmidt-Phillips tests show the temperature series to be trend stationary and the gas series with the exception of the CFC series to be I(1).

d. Cointegration

Cointegration analysis can determine whether the stochastic trends uncovered by univariate tests are shared by more than one series. Some cointegration procedures, including the structural time series approach and the Johansen methodology (Johansen, 1988, 1992, 1995; Johansen and Juselius, 1995), also can be used to test for the presence of stochastic trends in variables conditional on information in the other variables in the model. Typically, linear combinations of integrated process also are integrated. The residual from a regression of the two variables will be non-stationary. This violates the classical conditions for a linear regression. Such a regression is known as a spurious regression (Granger and Newbold, 1974). Correlation coefficients and t statistics for the regression are likely to show that there is a significant relation between the variables when none exists.

If two or more I(1) variables share a common stochastic trend they are said to cointegrate (Engle and Granger, 1987). That is, there is a linear combination of the variables that eliminates the stochastic trend, generating a stationary residual. This linear combination represents a long run equilibrium among the cointegrated variables. If variables tend to drift apart over time then it makes little sense to say that there is a meaningful relationship involving these variables alone (Enders,

[*] The full results are available from the authors on request. Tests were also carried out on emissions series - some were I(1) and some I(2).

1995).[*] If they do not cointegrate, the variables either have no meaningful relationship at all, or there are omitted variables, or some irrelevant integrated variables are present. A large literature discusses testing for cointegration and estimating cointegrated models (for surveys see Hamilton, 1994; Enders, 1995, Dickey and Rossana, 1994). The linear function that eliminates the stochastic trends is called the "matrix of cointegrating vectors".

Whereas I(1) variables are either cointegrated or not cointegrated, more complicated relations are possible among I(2) variables. Direct cointegration to a stationary residual is possible and is denoted CI(2,2) cointegration - the linear function removes a second order integrated trend (second number) from I(2) variables (first number). CI(2,1) cointegration occurs when the linear combination reduces the order of integration by one (second number) generating an I(1) residual. However, this residual may, in turn, cointegrate with the first differences of the variables. In this case, there may be a long-run equilibrium between the variables, but return to that equilibrium after perturbation is very slow.

A further implication of the cointegration concept is that if the variables have different orders of integration they cannot be cointegrated directly.[**] The differences in the order of integration found in the previous subsection (2c.) cast doubts on the existence of a direct relation between radiative forcing and temperature. The univariate tests indicate that the temperature data are I(1) while the trace gases are I(2). That is, the gases contain stochastic slope components that are not present in the temperature series. This result implies that there cannot be a linear long-run relation between gases and temperature. These univariate tests are not, however, conclusive.

3. Shortcomings of Univariate Stochastic Trend Tests

Theory provides a reason to believe that these univariate tests may not be able to identify the true order of integration of the temperature series. First, noise tends to increase the probability that the Dickey-Fuller and Phillips-Perron tests will reject the null hypothesis of a stochastic trend. Second, the Dickey-Fuller and other tests approximate the series as an autoregression which may not be appropriate.

The global temperature series is fairly noisy (Figure 1) as are the hemispheric series. As discussed by Enders (1995) and Hamilton (1994), the Dickey Fuller and other stochastic trend tests tend to

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[*] Most of the literature deals with linear relations. However, nonlinear cointegrating relations are also theoretically possible (Granger, 1993).

[**] A sub-group of variables can cointegrate to a residual with a lower order of integration and that residual can cointegrate with other variables of the same lower order of integration. For example a group of I(2) variables can cointegrate to an I(1) aggregate that then cointegrates with other I(1) variables to an I(0) (stationary) residual. Stern and Kaufmann (1997) find no evidence that such an aggregate exists among the trace gas variables found to be I(2).

reject the null too often when the true data generating process is a random walk with noise and the noise is large compared to the signal. The lower the signal to noise ratio, the higher the probability of a type I error (i.e. incorrect rejection of the null of a stochastic trend). This type of error is less likely for the relatively less noisy radiative forcing series. An I(1) series can be represented as:

$$y_t = \mu + A_t + \eta_t \tag{8}$$

$$A_t = A_{t-1} + \varepsilon_t \tag{9}$$

where ε_t and η_t are random error processes and A_t is the stochastic trend. σ_η^2 is the variance of η, and σ_ε^2 is the variance of ε. In a finite sample, reducing the signal to noise ratio $\sigma_\eta^2 / \sigma_\varepsilon^2$ increases the probability that the test will indicate that y_t is trend stationary--a type I error (Enders, 1995). Schwert (1989), Phillips and Perron (1988), and Kim and Schmidt (1990) confirm this result using Monte Carlo simulations.

The problem can also be considered in the context of ARIMA (AutoRegressive Integrated Moving Average) models. A wide range of time series models can be represented as an ARIMA model with finite lag lengths. The Dickey Fuller and related stochastic trend tests approximate the time series as a finite autoregression (i.e. AR(p) model). The accuracy of this approximation (which ignores the potential moving average part of the process) is depends on how close the MA part of the true process is to the boundary of the invertibility region. That is, how close the roots of the MA polynomial are to the unit circle (Harvey, 1993). Harvey (1993) argues that the roots of the MA polynomial are likely to be near the unit circle when the true process is I(2). For example, in the local linear trend model (equations (1) through (3)), which corresponds to a reduced form ARIMA(0,2,2) model, the variance of the slope disturbance (ζ_t) generally is small in relation to the variances of the other two error terms. This means that the MA part of the process is close to non-invertibility. "The net result is that distinguishing between I(1) and I(2) processes is likely to be very difficult in practice, with the AR based stochastic trend tests tending to favour I(1) specifications, even when I(2) models are appropriate." (Harvey, 1993, 134)

The presence of MA components also affects tests where the null hypothesis is an I(1) stochastic trend, and causes them to reject of the null far more often than indicated by the standard distributions (Pantula, 1991). Pantula found that the Dickey-Fuller test performed much better than the Phillips-Perron test, but still tended to reject the null too often. This result seems to be replicated in our data, where the Dickey-Fuller test may indicate the presence of a stochastic trend in the temperature series while the Phillips-Perron test clearly rejected the null.

4. Structural Time Series Approach

To further investigate the time series properties and dynamics of the hemispheric temperature series we use the structural time series modeling approach promoted by Harvey (1989). Structural time series models cover a wide range of models but all characterized by estimating trend, cyclical, seasonal, and noise components separately and directly. This means that in contrast to the traditional autoregressive models used in econometrics, hypotheses tests carried out on the model do not suffer from the biases discussed in section 3. The specific model we use is a vector autoregression with common stochastic trends (see Harvey, 1989, pp470-473). The stochastic trends are modeled using the local linear trend model in (1) through (3), while the noise processes (ε_t) are modeled using a vector autoregression - i.e. current values of the the error in the equation for dependent variable i (ε_{it}) are a linear function of its own past values and of the past errors in the equations for the other dependent variables.

Thus, the null hypothesis is that each series is stationary with a Gaussian error, while a large number of alternative hypotheses can be entertained including deterministic trends and I(1) or I(2) stochastic trends in some or all of the series. The method also can be used to estimate cointegrating vectors. For concreteness we describe the bivariate model we actually use rather than the general case. Using the terminology of state-space models, the measurement equations (equivalent to conventional regression equations but containing state variables that are not directly observed) are:

$$S_t = A_{1t} + \qquad + W_t \tag{10}$$

$$N_t = \theta A_{1t} + A_{2t} + Z_t \tag{11}$$

where S and N are the Southern and Northern Hemisphere temperature series. A_1 and A_2 are nonstationary state variables - the signal - and W and Z are stationary unobserved noise processes. A_1 is a possibly common stochastic trend, θ is an estimated fixed parameter. The exclusion of A_2 from the first equation is a necessary identifiability condition. The ordering of the dependent variables is essentially arbitrary - regardless of the ordering, the "true trends" can be recovered using a "factor rotation" (see for example Harman, 1976).

However, the specification of equations (10) and (11) may have a direct interpretation. The temperature signal associated with greenhouse gases and solar irradiance, which are relatively similar across the northern and southern hemisphere, may be represented by the shared trend A_1. A_2 which appears only in the northern hemisphere (eq. 12) may represent anthropogenic sources of tropospheric sulfates, which are emitted largely in the northern hemisphere, where they have their greatest effect (Kiehl and Briegleb, 1993).

A shared stochastic trend is not imposed on the model--the hypothesis that temperature in the northern and southern hemisphere shares a stochastic trend can be falsified. If the temperature data do not share a stochastic trend, θ will be zero. Sharing of a stochastic trend implies that the dependent variables are cointegrated. A variety of different forms of cointegration are possible depending on the nature of the estimated trends. If the trend A_1 is shared and is I(2) and A_2 is deterministic, the variables are CI(2,2) i.e. the cointegration relation completely eliminates the I(2) stochastic trend. If A_2 is I(1), the variables are cointegrated as CI(2,1) - the cointegration relation converts the I(2) trend to an I(1) residual. The stochastic trends are modeled by the following transition equations:

$$A_{it+1} = A_{it} + \lambda_{it} + \eta_{it} \qquad i = 1,2 \qquad (12)$$

$$\lambda_{it+1} = \lambda_{it} + \upsilon_{it} \qquad i = 1,2 \qquad (13)$$

where υ_i and η_i are stationary white noise processes. If the variance of υ_i is nonzero then A_i is an I(2) trend. If the variance of υ_i is zero then λ_i is a constant and A_i is a random walk with drift. If λ_{i0} is also zero then A_i is a driftless random walk. If both error variances are zero then A_i is deterministic. A second necessary identifiability condition is that the covariance matrix of (A, λ) is diagonal (Harvey, 1989). The noise processes are modeled as follows:

$$W_{t+1} = \sum_{j=0}^{p} \Phi_{1j} W_{t-j} + \sum_{j=0}^{p} \Psi_{1j} Z_{t-j} + \varepsilon_{1t} \qquad (14)$$

$$Z_{t+1} = \sum_{j=0}^{p} \Phi_{2j} W_{t-j} + \sum_{j=0}^{p} \Psi_{2j} Z_{t-j} + E_{21}\varepsilon_{1t} + \varepsilon_{2t} \qquad (15)$$

where the ε_i are white noise processes, p is the optimal lag length, and Φ and Ψ are matrices of coefficients. The model laid out in equations (10) through (15) is estimated using the Kalman filter. Under the assumption that the random errors are Gaussian, the Kalman filter is used to compute the likelihood function using the prediction error decomposition (Schweppe, 1965; Harvey, 1989). The fixed parameters: Φ, Ψ, θ, and the square roots of the covariance matrices of ε, η, and υ designated E, H, and U; are estimated by maximizing this likelihood function using the Davidon, Fletcher, Powell algorithm (Fletcher and Powell, 1963; Hamilton, 1994). Then the Kalman filter is used to predict the optimal values of A_{t+1}, W_{t+1}, and Z_{t+1} using the data in the sample up to period t. A second algorithm, the Kalman smoother, then calculates the optimal values of the state variables given the data in the entire sample. The initial conditions for the non-stationary variables, A and λ, are handled using the diffuse Kalman filter algorithm of de Jong (1988, 1991a, 1991b). This algorithm sets A_{i0} and λ_{i0} equal to zero with variance equal to the variances of their respective error processes. The Kalman smoother computes the actual optimal mean and variance of A_{i0} and are

λ_{i0} - these can take any value. This method can be used for any non-stationary linear model.* The variance of ε_1 was concentrated out of the likelihood function - i.e. E_{11} is set to one.

5. Results

a. Selection of Lag Length

An array of statistics used to select the optimal lag length, p (Table 1). The longest lag length considered was 5. The likelihood ratio statistic, which is distributed asymptotically as chi-square with 4(5-p) degrees of freedom, indicates that restrictions which reduce the lag length to 1 or 2 lags relative to 5 lags are rejected at the 10% level. Restrictions that reduce the lag length to 3 or 4 are not rejected. The Akaike Information Criterion (AIC) indicates that 3 lags is optimal while the Schwartz Bayesian Criterion (see Enders, 1995) indicates that one lag is the optimal lag length. This latter criterion usually indicates a shorter lag then the AIC. The Durbin-Watson statistic tests for first order serial correlation in the residuals and the Q statistic is a test of all autocorrelation coefficients up to the lag specified. The residuals in all models are not found to be serially correlated, though the residuals for models with lags of 3 to 5 are closer to white noise than those for models with lag lengths of 1 and 2. The one and two lag models also have several significant autocorrelations and partial autocorrelations among the first five autocorrelations and partial autocorrelations. The 3 lag model has just significant third autocorrelations and partial autocorrelations for the Northern Hemisphere equation. The 4 and 5 lag models have no significant autocorrelations or partial autocorrelations. These results are consistent with the Ljung-Box Multivariate Autocorrelation Test (Ljung and Box, 1978). This generalization of the Q statistic is approximately distributed as χ^2 with $n^2(T/4)$ degrees of freedom, where n is the number of measurement equations. The statistic is calculated over autocorrelations up to T/4 lags. Though none of the test statistics is significant at normal levels of significance, there is a big jump in the significance level between 2 and 3 lags. We choose 3 lags as this is the optimal lag according to both likelihood ratio and AIC criteria and appears to have slightly better residual properties than the one and two lag models.

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* For more details of the algorithms see de Jong (1991a, 1991b), Harvey (1989), or Hamilton (1994).

b. Estimates for the Optimal Model

Based on these results, we estimate a model that has 3 lags (Table 3). The standard errors are calculated from the Hessian of the likelihood function.* The Hessian was calculated using one sided finite differences. We find that the second differentiation required quite a large perturbation in order to get a negative definite Hessian.** Consequently, the results may not be particularly reliable on this account. The parameters of greatest interest are H, U, and θ. Both H_{11} and U_{11} are nonzero which means that A_1 is an I(2) trend. We note that using the t-test in Table 3, U_{11} is not formally significantly different from zero. However, univariate tests of the type described above show A_1 to be an I(2) variable. H_{22} is nonzero, but U_{22} is zero. Therefore, A_2 is an I(1) trend. The two temperature series cointegrate as CI(2,1), A_2 being the long-run cointegration residual. The estimate of θ is 1.64821; the cointegrating relationship (which eliminates the common trend) normalized on Northern Hemisphere temperatures is therefore:

$$N_t - 1.64821\, S_t = A_{2t} \tag{16}$$

This implies that the common trend has a 65% greater impact on Northern Hemisphere temperatures then on Southern Hemisphere temperatures. If this common trend is associated with the radiative forcing due to greenhouse gases and solar irradiance this difference in climate sensitivity would be expected due to differences in land/water ratios and other factors between the two hemispheres. $\sigma^2\varepsilon_1$ is the estimate of the variance of ε_1 which was concentrated out of the likelihood function - i.e. it is computed by the Kalman filter rather than being a parameter estimated by ML. All the error variances are scaled by this variance. The remaining parameters are best summarized in terms of the companion matrix (Hansen and Juselius, 1995). The maximum eigenvalue of this matrix is 0.74365, showing that the noise process is indeed stationary.** Most of these parameters are formally significantly different from zero.

c. Origins of the Stochastic Trends

In this section we compare the estimated stochastic trends to known series that may have an effect on temperature. Figure 2 shows the smoothed estimates of A_1 compared to the Southern Hemisphere temperature series. Figure 3 compares the smoothed estimates of A_2 with estimates of the radiative forcing due to sulfur emissions. The sulfur emissions are scaled using the regression equation:

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* $V = (-H)^{-1}$ where H is the Hessian and V is the estimated covariance matrix.

** i.e. the gradient itself was estimated using a perturbation of 1.0e-06 on each parameter, but the perturbation on parameters which were then evaluated for their impact on the gradient was 2.0e-04. A perturbation of 1.0e-04 resulted in one positive eigenvalue in the Hessian.

** A maximum eigenvalue of 0.9 or greater might be taken as evidence of a unit root in the process.

$$A_{2t} = 0.4035 + 0.3868\ SO_{xt} \qquad (17)$$

which was estimated using ordinary least squares. The relationship between the series in Figure 3 is suggestive though not conclusive, as the sulfur series does not cointegrate with A_{2t}, particularly in the early years of the sample. The Durbin-Watson statistic, which can be used as a simple cointegration test (Engle and Granger, 1987) is 0.1805, far below the critical value of 0.386 at the 5% level of significance or the critical value of 0.322 for the 10% level of significance. Figure 4 shows the Durbin Watson statistic for regressions on sample periods starting in the year indicated and ending in 1994. Cointegration clearly improves when the pre-1900 data (which are expected to be less reliable) are dropped from the sample.

We also test whether the first trend might be related to a global warming signal due to the radiative forcing of greenhouse gases and changes in solar irradiance. First, we estimate a simple regression of the first trend on a variable for the aggregate radiative forcing due to carbon dioxide, methane, nitrous oxide, CFC11, CFC12, and solar irradiance. The Durbin Watson statistic for this regression is 0.061543. Though this statistic also improves when early data are removed, it never exceeds the critical level (Figure 4). However, as both temperature series are I(2) it is possible that temperature and radiative forcing CI(2,1) cointegrate to an I(1) disequilibrium. This is reasonable because temperature response to changes in radiative forcing will be spread out over a long period. The Durbin-Watson test statistic for a regression of the first difference of the first trend on the first difference of radiative forcing is 0.905122. This statistic exceeds the critical level, which indicates that these series do cointegrate. As in the case of the regression between sulfates and A_2, the Durbin-Watson statistic also increases somewhat when pre-1900 data are dropped from the sample.

These results are tentative. However, they are supported by previous work (Kaufmann and Stern, 1997), where we used direct regression methods to show Granger causality from radiative forcing variables to temperature.

6. Conclusions

The results presented in this paper indicate that there may be a global warming signal present in hemispheric temperature series. Univariate stochastic trend tests appear to have difficulty in detecting this trend due to the low signal to noise ratio of the temperature series. The difference between the temperature series are possibly due to sulfur emissions in the Northern Hemisphere and the greater climate sensitivity of Northern Hemisphere temperatures. These results reinforce both our own previous work (Kaufmann and Stern, 1997) and other work which suggested these hypotheses (Wigley, 1989). While connection of the common stochastic trend in the temperature series to radiative forcing due to greenhouse gases and solar irradiance is tentative, our work shows that such a global warming signal could be present in the temperature series. This is contrary to the interpretation of Woodward and Gray (1993, 1995) that the presence of a stochastic trend in temperature is evidence that the current warming may not continue.

Acknowledgements

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APPENDIX I: DATA SOURCES

We have assembled an annual time series data set for the period 1856 to the present for the variables described below.

Temperature

We examine three temperature indicators - global mean annual temperature, and series for the Northern and Southern Hemispheres separately. These data have not been adjusted for ENSO. These data are available from (Jones *et al*., 1994).

Carbon Dioxide

Data for direct observations for the atmospheric concentration of carbon dioxide are available from the Mauna Loa observatory starting in 1958. Prior to 1958, we used data from the Law Dome DE08 and DE08-2 ice cores (Etheridge *et al*. 1996). We interpolated the missing years using a natural cubic spline and two years of the Mauna Loa data (Keeling and Whorf 1994) to provide the endpoint. The data set can be updated in a consistent manner based on annual observations from Mauna Loa.

Methane

Indirect observations for the atmospheric concentration of methane are available from the Law Dome ice core (Etheridge *et al*. 1994). These data are available starting in 1841 and end in 1978. Observations are not available for every year and some years have multiple observations. We use a cubic spline to generate a consistent set of annual observations. From 1968 on we combine these data with the Battle et al. (1996) firn data to obtain a smooth series. The values in the Battle *et al*. series are scaled down to match the levels in the ice core. 1979-83 is based on the firn data. 1983 is based on actual observations at Palmer Station (Dlugokencky *et al*., 1994). 1984-86 are observations from Cape Grim (Dlugokencky *et al*., 1994). The remainder of the data - 1987-1995 - are also from Cape Grim but collected by Prinn et al. (1990) in the GAGE/AGAGE network. The latter data were downloaded from CDIAC (Prinn *et al*., 1997) and are described in Prinn *et al*. (1990). Accounting for the effects of tropospheric ozone and stratospheric water vapor due to methane (Kattenberg *et al*., 1996) and the overlap with nitrous oxide, we calculate that radiative forcing is given by approximately 0.0387 ($\sqrt{M_t}$ - $\sqrt{M_{1860}}$) where M is in ppbv.

CFC's

Prather *et al*. (1987), have generated estimates for years prior to 1978 based on historical emissions and a general model of atmospheric mixing. Direct observations for the atmospheric concentration of CFC-11 and CFC-12 are available starting in 1978 (Cunnold *et al*., 1994). For CFC-11 we used the data for Adrigole and Mace Head in Ireland. Missing years were filled using the rates of change in the data from the Barbados station. For CFC-12 we used the data from

Barbados which more closely match the Prather *et al*. data for this gas. Including the radiative forcing due to ozone depletion (Kattenberg *et al*., 1996, Wigley and Raper, 1992) gives the following formulae:

CFC-11 $0.22\ y - 0.0552\ (3y)^{1.7}$
CFC-12 $0.28\ z - 0.0552\ (2z)^{1.7}$

where y and z are in parts per billion.

Nitrous Oxide

Data from 1978 to the present are observations from Cape Grim in the ALE/GAGE/AGAGE network (Prinn *et al*., 1990; Prinn *et al*., 1997). Pre-1978 is based on data from the H15 Antarctica ice core reported in Machida *et al*. (1995) and the Battle *et al*. (1996) firn data. We discard a number of observations from the Machida *et al*. (1995) data based on the fit with the Battle *et al*. (1996) firn data and fitted a cubic spline to the remaining data. Radiative forcing is assumed to be 0.1325 ($\sqrt{N_t} - \sqrt{N_{1860}}$) where N is in ppbv. The coefficient is reduced from 0.14 to account for the overlap with methane.

Aerosols

We use estimates of stratospheric aerosols from Sato *et al*. (1993). The radiative forcing due to these emissions has been estimated by L. D. Harvey (personal communication).

We use estimates of anthropogenic emissions of SOx rather than ice core records of tropospheric sulfate aerosol densities. For 1860 to 1990 we use estimates prepared by A.S.L. and Associates (1997). The estimates are updated to 1994 using methods documented in Stern and Kaufmann (1996). Radiative forcing is assumed to be $-.3\ (S_t / S_{1990})\ -.8\ \ln(1 + S_t/42) / \ln(1 + S_{1990}/42)$ where S is in megatonnes (Kattenberg *et al.*, 1996; Wigley and Raper, 1992). The emissions are modified to account for the increase in stack heights over time (Wigley and Raper, 1992).

Solar Activity

The effect of solar activity on the planetary heat balance is represented using the index of solar irradiance assembled by Lean *et al*. (1995). Radiative forcing is linear in irradiance and equal to .175 times the change in irradiance (Shine *et al*., 1991)

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Table 1 Univariate Tests for Order of Integration

Variable	Dickey-Fuller	Phillips-Perron	Sch: midt-Phillips	KPSS
Temperature - nhem	I(1)	I(0)	I(0)	I(1)
Temperature - shem	I(1)	I(0)	I(0)	I(1)
Temperature - global	I(1)	I(0)	I(0)	I(1)
CO_2	I(2)	I(1)	I(1)	I(2)
CH_4	I(1)	I(1)	I(1)	I(2)
CFC11	I(2)	I(2)	I(2)	I(2)
CFC12	I(2)	I(2)	I(2)	I(2)
N_2O	I(1)	I(1)	I(1)	I(2)
Sun	I(1)	I(1)	I(1)	I(1)
Stratospheric Sulphates	I(0)	I(0)	I(0)	I(0)
SOx emissions	I(1)	I(1)	I(1)	I(1)

Forcing variables are transformed into radiative forcing series. I(x): Integrated of order x.

Table 2 Selection of Lag Length

# of Lags	Log Likelihood	Likelihood Ratio Test	AIC	SBC	Durbin Watson	Q(35)	Ljung-Box Multivariate Auto-correlation Test
1	610.7901	31.61672 (0.011)	-1199.58	-1167.14	1.7293 1.7824	34.3559 (0.499) 28.1243 (0.789)	167.0809 (0.135)
2	616.7613	19.67432 (0.074)	-1203.52	-1159.29	2.4134 2.0716	38.6298 (0.309) 39.5637 (0.273)	165.6472 (0.105)
3	624.4733	4.25026 (0.834)	-1210.95	-1154.92	2.1023 2.1820	24.7186 (0.902) 32.6332 (0.583)	131.4171 (0.686)
4	625.5760	2.04498 (0.727)	-1205.15	-1137.33	2.1160 2.1545	24.2980 (0.912) 23.4163 (0.932)	119.4982 (0.842)
5	626.5984	-	-1199.20	-1119.58	2.0944 2.0463	26.2477 (0.857) 23.7483 (0.925)	117.6875 (0.809)

Likelihood ratio test is for restriction relative to five lags - significance level in parentheses. For Durbin Watson and Q statistics, the first number is for the Southern Hemisphere equation and the second statistic is for the Northern Hemisphere equation. For the Q statistic the figure in parentheses is the level of significance.

Table 3 Parameter Estimates for Optimal Model

Parameter	Estimate	Standard Error	t-statistic	Parameter	Estimate	Standard Error	t-statistic
θ	1.64821	0.34714	4.74797	Ψ_{21}	0.06296	0.06236	1.00962
Φ_{11}	0.49045	0.05921	8.28323	Ψ_{22}	0.00463	0.05921	0.07820
Φ_{12}	-0.11735	0.05956	-1.97028	Ψ_{23}	-0.37682	0.05712	-6.59699
Φ_{13}	0.30638	0.05711	5.36473	E_{21}	0.45014	0.07373	6.10525
Φ_{21}	0.34006	0.07360	4.62038	E_{22}	1.08918	0.07483	14.55539
Φ_{22}	-0.37439	0.07234	-5.17542	H_{11}	0.25698	0.05889	4.36373
Φ_{23}	0.30687	0.07324	4.18992	H_{22}	0.19507	0.08798	2.21721
Ψ_{11}	-0.06653	0.04895	-1.35914	U_{11}	0.00409	0.00649	0.63020
Ψ_{12}	-0.13863	0.04929	-2.81254	U_{22}	0	n.a.	n.a.
Ψ_{13}	-0.13401	0.04822	-2.77914	$\sigma^2\varepsilon_1$	0.0788	n.a.	n.a.

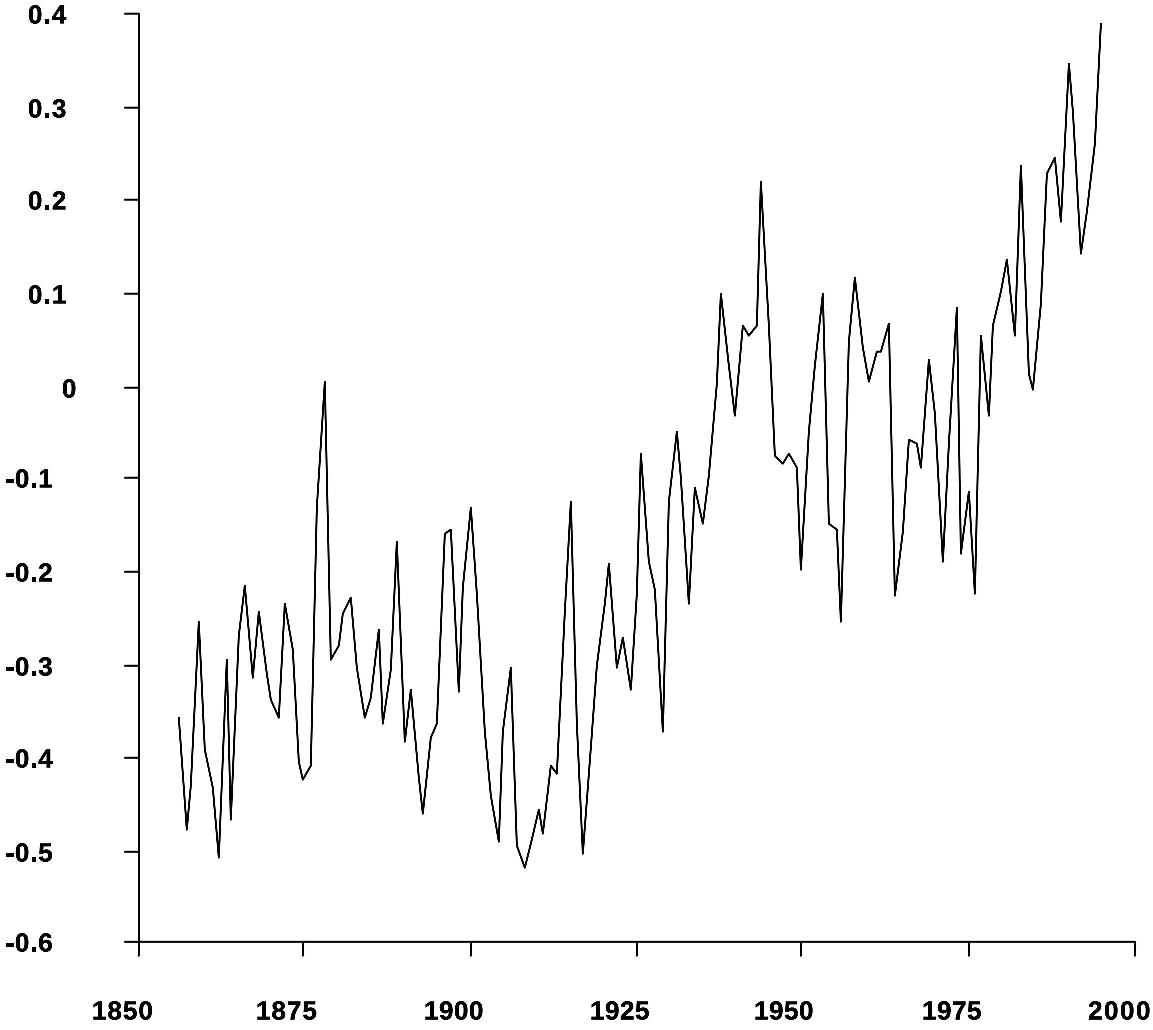
Figure Captions

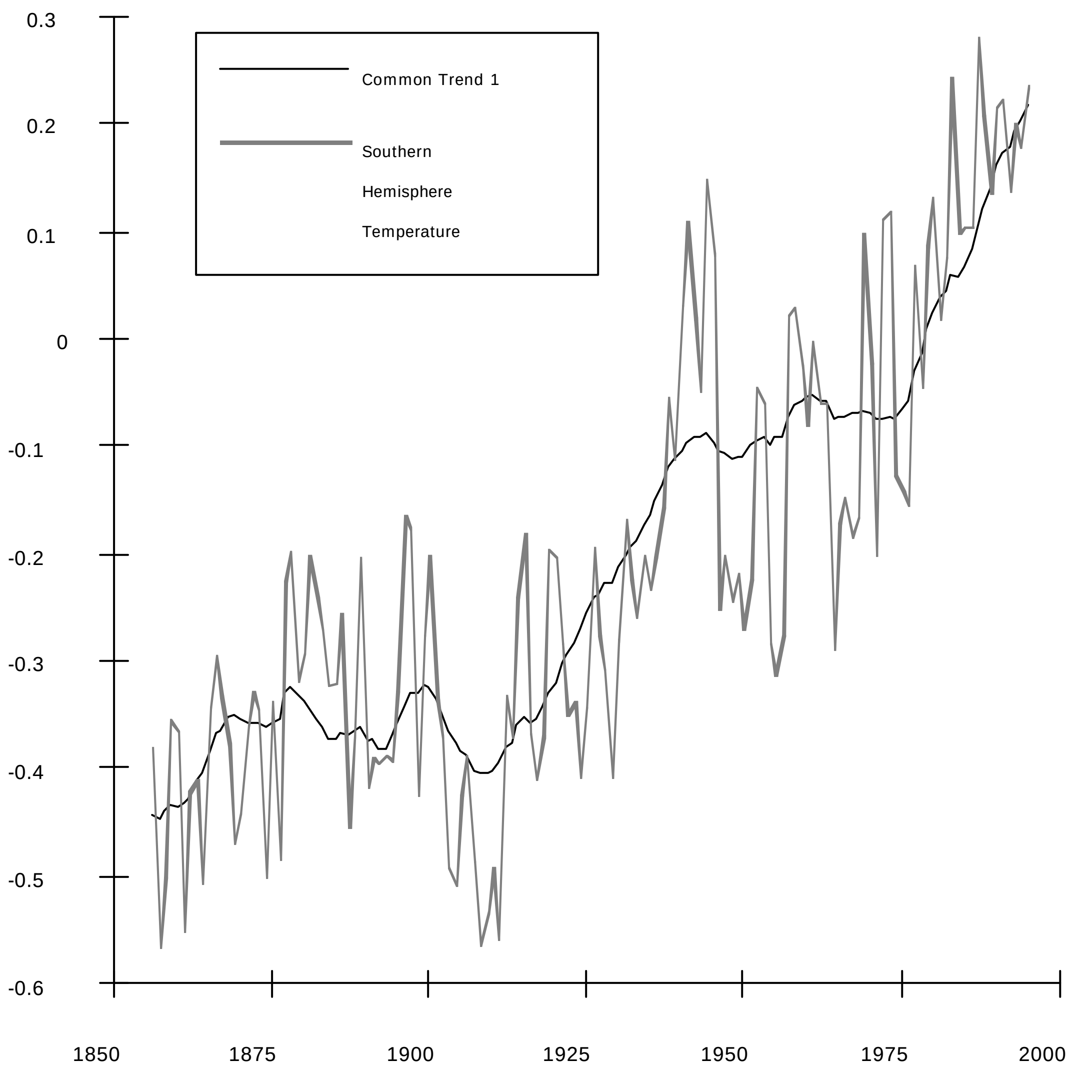
Figure 1
Global Temperature 1856-1995

Figure 2
Smoothed Estimates of the Common Trend and Southern Hemisphere Temperature.

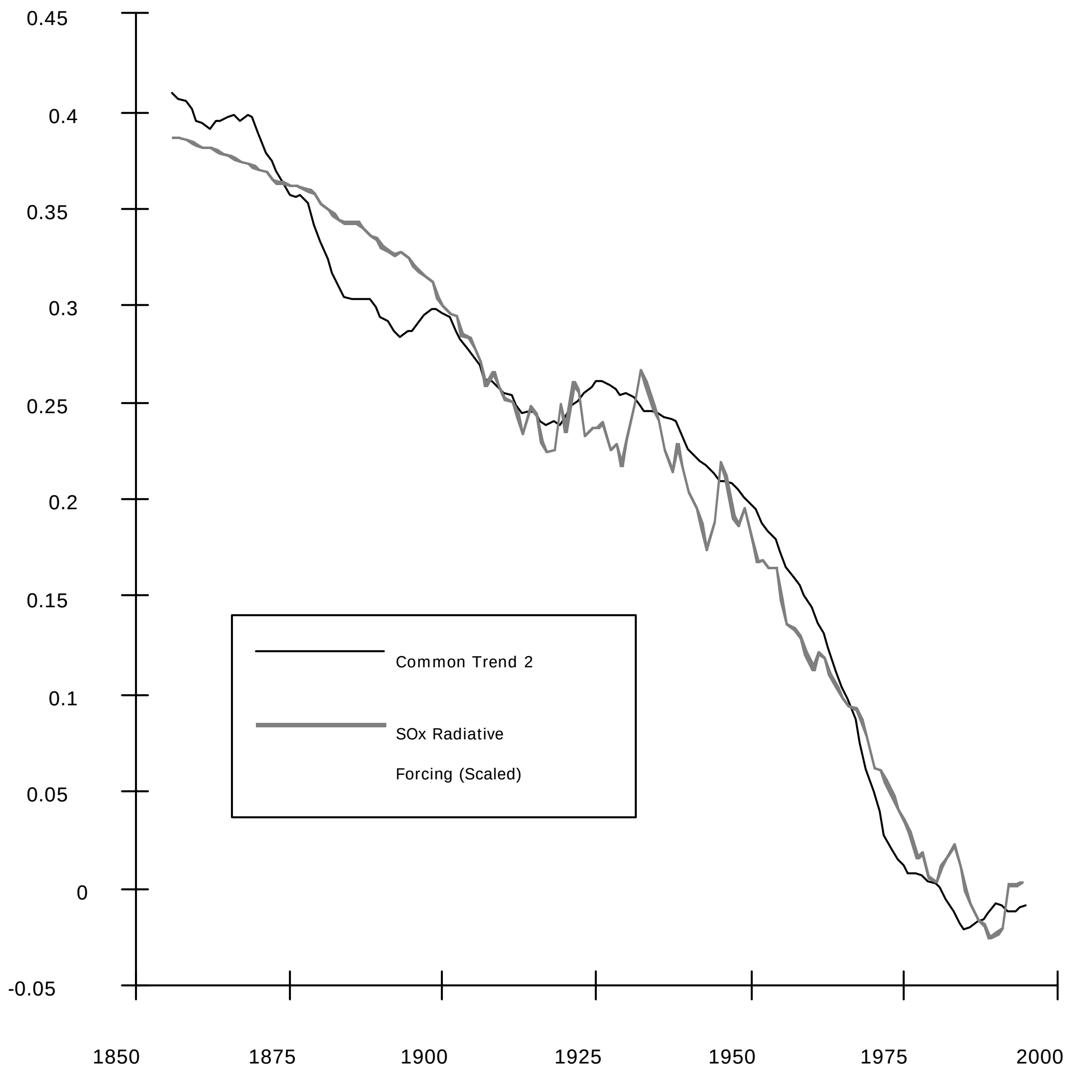
Figure 3
Smoothed Estimates of the Second Stochastic Trend and Estimates of Radiative Forcing Due to Sulfur Emissions.

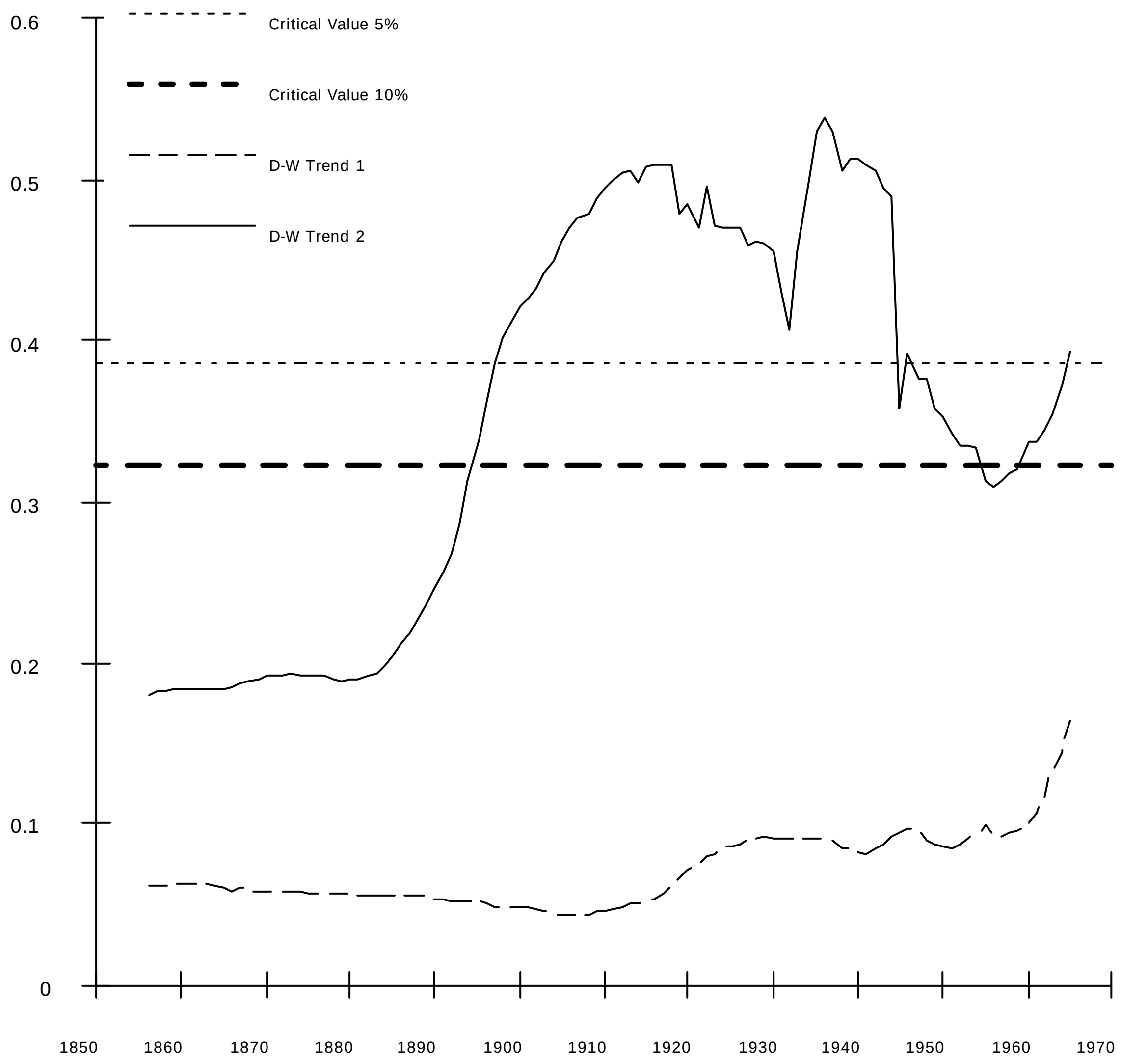
Figure 4
Durbin Watson Cointegration Statistics for Regressions of Common Trends on Explanatory Variables. (In each case the sample used in the regression starts in the year indicated and ends in 1995).


0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
1850
1875
1900
1925
1950
1975
2000



Common Trend 1
Southern
Hemisphere
Temperature
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
1850
1875
1900
1925
1950
1975
2000


0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
1850
1875
1900
1925
1950
1975
2000
Common Trend 2
SOx Radiative
Forcing (Scaled)


0.6
0.5
0.4
0.3
0.2
0.1
0
Critical Value 5%
Critical Value 10%
D-W Trend 1
D-W Trend 2
1850
1860
1870
1880
1890
1900
1910
1920
1930
1940
1950
1960
1970