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Cointegration analysis of hemispheric temperature relations

Robert K. Kaufmann
Center for Energy and Environmental Studies, Boston University, Boston, Massachusetts, USA

David I. Stern
Centre for Resource and Environmental Studies, Australian National University, Canberra, ACT, Australia

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[1] We use cointegration procedures that are designed to estimate and test relations among integrated time series to develop a model of the relation between surface temperature and the radiative forcing of solar irradiance, greenhouse gases, and tropospheric sulfates. We use this model to test some basic hypotheses regarding the relation between surface temperature and radiative forcing. We find that there is a statistically meaningful relation between surface temperature and changes in the radiative forcing associated with natural variability and human activity. We also find that hemispheric temperatures cannot be explained by hemispheric forcings alone: Hemispheric temperatures are linked. Differences in hemispheric temperatures are associated with differences in the hemispheric temperature effects of greenhouse gases, anthropogenic sulfur emissions, and solar irradiance. Estimates for the temperature sensitivity (ΔT_{2x}) are consistent with the middle and lower range of values estimated by physically based models. *INDEX TERMS:* 1610 Global Change: Atmosphere (0315, 0325), 1620 Global Change: Climate dynamics (3309), 1650 Global Change: Solar variability; *KEYWORDS:* atmosphere, radiative forcing, greenhouse gases, solar irradiance, temparature, sulfur emissions

1. Introduction

[2] Evidence is mounting that changes in global surface temperature can be attributed to human activities that increase the atmospheric concentration of greenhouse gases and tropospheric sulfates [*Santer et al.*, 1996a, 1996b]. This evidence comes from two sources: physically based simulation models of the climate system and statistical analyses of historical data. Evidence for the effect of human activity is provided by the ability of climate models to improve their simulation of the spatial/temporal temperature record by including the radiative forcing due to changes in greenhouse gases and tropospheric sulfates [*Cowley*, 2000; *Tett et al.*, 1999; *Wigley et al.*, 1998; *Santer et al.*, 1996a, 1996b; *Mitchell et al.*, 1995].

[3] The time series for temperature and many radiative forcing variables exhibit strong trends; therefore classical linear regression techniques may indicate a relation among these variables whether or not a relation exists [*Granger and Newbold*, 1974]. These techniques cannot therefore be used in isolation [e.g., *Tol*, 1994; *Tol and de Vos*, 1993] to determine whether human activity affects temperature. The International Panel on Climate Change previously argued that [*Folland et al.*, 1992, p. 163] "rigorous statistical tools do not exist to show whether relationships between statistically nonstationary data of this kind are truly statistically significant." The inability to determine whether relations among nonstationary variables are statistically significant also presented considerable problems for macroeconomists. Recently, time series econometricians have defined the concept of cointegration and developed techniques to detect and model cointegrating relations among a class of nonstationary variables: integrated or stochastically trending variables [e.g., *Engle and Granger*, 1987; *Johansen*, 1988; *Johansen and Juselius*, 1990; *Stock and Watson*, 1993]. As the name implies, integrated variables are functions of random walks and exhibit a stochastic rather than deterministic trend. Thus the classic approach to estimating relations among trending variables, detrending by removing a linear trend, is inappropriate, and the more sophisticated cointegration methodology, described in sections 2 and 4, must be used.

[4] In this paper, we estimate a time series model of the relation between temperature and various components of radiative forcing using the cointegration procedures developed by Søren Johansen and associates [e.g., *Johansen*, 1988; *Johansen and Juselius*, 1994, 1990]. This method allows for statistical testing under appropriate assumptions about nonstationary behavior. The results add to the growing body of statistical evidence [*Kuo et al.*, 1990; *Kaufmann and Stern*, 1997; *Wigley et al.*, 1998; *Stern and Kaufmann*, 2000] for the effect of human activity on surface temperature by finding a statistically meaningful link between temperature and greenhouse gases, tropospheric sulfates, and solar activity that is consistent with the physical mechanism(s) by which radiative forcing is thought to affect temperature.

[5] The methodology and results are described in the following six sections. Section 2 examines the time series properties of the temperature and radiative forcing time series. Section 3 describes the potential pitfalls associated with statistical analyses of nonstationary data. Section 4 describes how we use the method developed by *Johansen and Juselius* [1994, 1990] and *Johansen* [1988] to estimate the model and test hypotheses. The results are described in section 5. Section 6 describes how these results are consistent with a relation between surface temperature and the radiative forcing of greenhouse gases, tropospheric sulfates, and solar irradiance. The conclusion (section 7) discusses ongoing research that may mitigate some of the limitations of the research described in this paper.

2. Time Series Properties of Climate Data

[6] There are various forms of nonstationarity; in this paper we consider trending series. Because of this trend the variable has no population mean, and its variance is theoretically infinite. Sample means are time varying and variances increase with the sample size. On the other hand, a stationary variable has a constant mean and

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Table 1. Time Series Properties of Climate Variables as Indicated by the Augmented Dickey-Fuller Statistic[a]

	Augmented Dickey-Fuller Statistic		
Variable	Levels	First Difference	Classification
NHEM	−2.81	(−11.67)	I(1)
SHEM	−3.40	(−9.67)	I(0)
RFGG	1.57	(−3.88)	I(1)
RFSOXNH	−0.91	(−6.61)	I(1)
RFSOXSH	−0.23	(−8.17)	I(1)
SUN	−2.57	(−7.72)	I(1)
RFSSNH	(−4.34)		I(0)
RFSSSH	(−4.13)		I(0)

[a] Values that exceed the 0.05 threshold (−3.42) are in parentheses. The 1% critical value is 4.04.

variance. The trend in a time series may be deterministic and/or stochastic. A deterministic trend is a simple function of time such as a linear, quadratic, or exponential trend in time. A stochastic trend is an integrated series of random variables so that its rate of change is irregular.

[7] The simplest example of a stochastic trend is a random walk, which is a discrete time version of the continuous time Brownian motion, and is given by

$$Y_t = \lambda Y_{t-1} + \varepsilon_t, \qquad (1)$$

in which the autoregressive coefficient $\lambda = 1$ and ε is a normally distributed random error term, the innovations, whose mean may be nonzero. Stochastic trends are characterized by long-term memory; the effects of innovations do not fade over time. More complex stochastically trending variables may have additional stationary noise components and deterministic or stochastic slopes and may also be related to other integrated variables.

[8] While the unforced climate system might be expected to be stationary, changes in radiative forcing might introduce a stochastic trend in temperature if the radiative forcing variables have a stochastic trend. This is likely because the concentrations of trace gases and sulfate aerosols are driven by anthropogenic emissions, which are determined by the stochastic trends that characterize many macroeconomic time series. Furthermore, carbon dioxide has a very long residence time in the atmosphere of around a century [*Moore and Kaufmann*, 1992], and so its autocorrelation coefficient is close to one. This is true despite the fact that natural flows of CO_2 in and out of the atmosphere are approximately equal and anthropogenic emissions of carbon dioxide are 1–2 orders of magnitude smaller than these natural flows.

[9] The random walk in (1) is integrated of order 1, symbolized as I(1). This terminology indicates that differencing the series once yields a nonintegrated series. A nonintegrated series that either is stationary or contains a deterministic trend is termed I(0). Integrating an I(1) variable generates a so-called I(2) series which must be differenced twice to yield a stationary series.

[10] We use the augmented Dickey-Fuller (ADF) test [*Dickey and Fuller*, 1979] to classify the time series for temperature and radiative forcing as I(0), I(1), or I(2). To carry out the Dickey-Fuller test, we estimate the following regression for each variable of interest y:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{I=1}^{s} \delta_i \Delta y_{t-i} + \varepsilon_t, \qquad (2)$$

where Δ is the first difference operator, t is a linear time trend (which is used to represent a possible deterministic trend), ε is a random error term, and the coefficient $\gamma = \lambda - 1$. The null hypothesis for the ADF test is that the series is at least I(1). The ADF test evaluates this null, $\gamma = 0$, i.e., $\lambda = 1$, by comparing the t statistic for γ against a nonstandard distribution. If we reject the null hypothesis for the undifferenced series, then that series is I(0). If we can only reject the null hypothesis for the differenced series, then that series is I(1), and similarly, a series is I(2) if only the second difference of the series is found to be I(0). The number (s) of augmenting lagged dependent variables Δy_{t-i} is selected using the Akaike information criterion [*Akaike*, 1973].

[11] We apply the ADF test to each of the time series that we use in the cointegration model described in section 4. These variables are (1) RFGG, an aggregate of the radiative forcing of all major greenhouse gases: carbon dioxide, methane, CFC11, CFC12, and nitrous oxide, (2) RFSOXNH, the radiative forcing of anthropogenic sulfur emissions in the Northern Hemisphere, (3) RFSOXSH, the radiative forcing of anthropogenic sulfur emissions in the Southern Hemisphere, (4) RFSUN, the radiative forcing of solar irradiance, (5) NHEM, mean land and sea surface temperature in the Northern Hemisphere, (6) SHEM, mean land and sea surface temperature in the Southern Hemisphere, (7) RFSSNH, the radiative forcing of stratospheric sulfates in the Northern Hemisphere, and (8) RFSSSH, the radiative forcing of stratospheric sulfates in the Southern Hemisphere. The sources for each of these variables and the method used to calculate radiative forcing are described by *Stern and Kaufmann* [2000].

[12] The ADF test indicates that the times series properties of the temperature and radiative forcing data vary (Table 1). The forcing variables RFGG, RFSOXNH, RFSOXSH, and RFSUN are all I(1). The temperature time series for NHEM and SHEM are I(1), but just barely so. The ambiguity of the ADF test result is consistent with the results of previous research and alternative test procedures [*Woodward and Gray*, 1995; *Bloomfield and Nychka*, 1992; *Stern and Kaufmann*, 1999]. The multivariate version of the ADF that we carry out in section 4 as part of the cointegration modeling exercise confirms that both temperature series are I(1). The series for the radiative forcing of stratospheric sulfates, RFSSNH and RFSSSH, are I(0).

3. Statistical Analysis of Data With Stochastic Trends

[13] In section 4 we develop a model that specifies surface temperature in the Northern and Southern Hemispheres as a function of the radiative forcing of greenhouse gases, anthropogenic sulfur emissions, solar irradiance, and stratospheric sulfates. Because these time series contain stochastic trends, classical regression techniques may indicate a statistically meaningful relation between temperature and radiative forcing even if there is no relation between these variables [*Granger and Newbold*, 1974]. The potential for misinterpreting regression results is caused by the presence of a stochastic trend, which affects the distribution of test statistics [*Phillips*, 1986]. Typically, linear combinations of time series that each contain a stochastic trend also contain a stochastic trend so that the residual from a regression of integrated variables is also nonstationary. This violates the classical conditions for a linear regression. Such a regression is known as a spurious regression [*Granger and Newbold*, 1974]. When evaluated against standard distributions, the correlation coefficients and t statistics for a spurious regres-

sion are likely to show that there is a significant relation between the variables when in fact none exists.

[14] To avoid spurious regressions, time series econometricians use the notion of cointegration. If two or more series that contain stochastic trends have a functionally dependent relation, the stochastic trends present in some of the series also will be present in the others. A common stochastic trend can be represented by

$$y_t = A_t + \varepsilon_t, \quad (3)$$

$$z_t = \theta A_t + \zeta_t, \quad (4)$$

$$A_{t+1} = A_t + \beta + \eta_t, \quad (5)$$

where ε_t, η_t, and ζ_t are stationary (but possibly autocorrelated) processes with mean zero. A_t (with deterministic slope β) is a random walk, which is the stochastic trend that is present in both y and z. Both time series y_t and z_t share the trend A_t and differ only by the scaling coefficient θ and the stationary noise components ε_t and ζ_t. Their nonstationary component is identical up to the scaling factor θ. Therefore it is highly likely that either of these variables, y_t or z_t, drives the other, that there is a mutual causation, or that a third factor drives them both.

[15] This shared trend implies that there will be at least one linear combination of the series that is stationary so that there is no stochastic trend in the residual. This phenomenon is known as cointegration [*Engle and Granger*, 1987]. In (3)–(5) the linear coefficients that eliminate the stochastic trend are $-\theta$ and 1. Multiplying (3) by $-\theta$ and adding (3) to (4) yields

$$z_t - \theta y_t = \zeta_t - \theta\varepsilon_t. \quad (6)$$

Because $\zeta_t - \theta\varepsilon_t$ is stationary, the long-run equilibrium is $z_t = \theta y_t$. In the short run the two variables can drift apart, but over time they will return to the long-run equilibrium. The vector $[-\theta\ 1]'$ is called the cointegrating vector.

[16] Equations (3)–(5) illustrate the pitfalls associated with conventional techniques for estimating relations among trending variables. Detrending the variables by removing a linear time trend from y and z is inappropriate because the resulting series still are integrated. Similarly, differencing the time series is inappropriate because it removes the common long-run driving trends. As a result, a regression of the first differences of the variables estimates the short-run relation only. A lack of cointegration indicates that a regression is spurious. Spurious regressions occur when the series in question have no relation, when a number of series may be related but an additional series (or series) that contains a stochastic trend also is required to fully explain the dependent variable(s), or when the relation among the variables is highly nonlinear. Regardless of the cause for noncointegration, there will be a stochastic trend in the dependent variable that is not shared with the explanatory variables. Irrelevant integrated series can be eliminated by setting their coefficients in the cointegrating matrix to zero.

4. Cointegration Methodology

[17] To determine whether surface temperature is related to radiative forcing in a statistically meaningful manner, we determine whether these data cointegrate. Analysts have developed several methods to test for cointegration and to estimate cointegrating models [*Stock and Watson*, 1993; *Johansen*, 1988; *Johansen and Juselius*, 1990; *Engle and Granger*, 1987]. We use the full information maximum likelihood method developed by Søren Johansen and his associates [*Johansen*, 1988; *Johansen and Juselius*, 1990] and coded by *Hansen and Juselius*, [1995]. We chose this method because it can be used to estimate multiple cointegrating relations that may exist among surface temperature and the various components of radiative forcing and it can identify how disequilibrium in the long-run relations between temperature and radiative forcing affects annual changes in temperature and how short-run changes in stratospheric sulfates affect surface temperature.

[18] The model assumes that the data can be represented by a vector autoregression (VAR) in levels; that is, each variable is regressed on lags of itself and of all other variables in the model, which can be represented as

$$\hat{\mathbf{y}}_t = \mathbf{B}_1\mathbf{y}_{t-1} + \ldots + \mathbf{B}_k\mathbf{y}_{t-k} + \boldsymbol{\mu} + \boldsymbol{\delta}_t + \boldsymbol{\Phi}\mathbf{d}_t + \boldsymbol{\varepsilon}_t\ , \quad (7)$$

in which $\hat{y}$ is a vector of I(1) variables whose behavior is being modeled (in our model this vector includes NHEM and SHEM), $\mathbf{y}$ is the vector of all I(1) variables (in our model this vector includes NHEM, SHEM, RFGG, RFSOXNH, RFSOXSH, and RFSUN), k is the number of lags, $\mathbf{B}$ and $\boldsymbol{\Phi}$ are matrices of coefficients to be estimated, $\boldsymbol{\mu}$ and $\boldsymbol{\delta}$ are vectors of coefficients to be estimated, $\mathbf{d}$ are I(0) variables (in our model this vector includes RFSSNH and RFSSSH), and $\boldsymbol{\varepsilon}$ is a vector of error terms with a multivariate normal distribution with no serial correlation and constant variance over time [*Hansen and Juselius*, 1995].

[19] Cointegration imposes restrictions on the coefficients of the VAR. To test these restrictions and to estimate the coefficients of the cointegrating vectors and the loading matrix, the VAR is reformulated (by rearranging variables, not by differencing: (7) and (8) are identical but have different parameterizations) as a vector error correction model (VECM):

$$\Delta\hat{\mathbf{y}}_t = \Gamma_1\Delta\mathbf{y}_{t-1} + \ldots + \Gamma_{k-1}\Delta\mathbf{y}_{t-k+1} + \alpha\beta'[1, t, \mathbf{y}_{t-1'}]' + \boldsymbol{\Phi}d_t + \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t\ . \quad (8)$$

For our model, (8) specifies the first differences of the hemispheric temperature data (we do not estimate the equations for the other variables), which are stationary, as a linear function of lagged values of the first differences of the temperature data and the four radiative forcing variables, which also are stationary, and stationary linear combinations of the temperature and radiative forcing variables, which constitute the cointegrating relations. The matrix of cointegrating vectors (explained in section 3) is given by β'. A loading matrix that indicates how each cointegrating relation affects annual changes in Northern or Southern Hemisphere temperature is given by α.

[20] If the stochastic trends in the data for the radiative forcing of greenhouse gases, anthropogenic sulfur emissions, and solar irradiance are solely responsible for the stochastic trend(s) in temperature over the last 130 years, there should exist a linear combination of hemispheric temperatures and the relevant radiative forcing variables that is stationary. This cointegrating relation represents the long-run equilibrium relation between temperature and radiative forcing. When this cointegrating relation is equal to zero, temperature and radiative forcing are said to be in long-run equilibrium.

[21] If there are no cointegrating relations, the matrix $\alpha\beta'$ will have rank zero. If all the variables in y already are stationary, then this matrix will be full rank. Intermediate ranks indicate the number of independent cointegrating vectors β. After estimating an unrestricted version of (8) the Johansen procedure tests the rank of $\alpha\beta'$ using an eigenvalue procedure to determine the number of cointegrating vectors. Once the number of vectors is selected, further hypotheses are tested by restricting the parameters in α and β. These tests are described in detail and applied in section 5.

[22] While the coefficients of β represent the long-run equilibrium relations among variables, elements of α indicate how disequilibrium in the cointegrating relations affects the annual rate of temperature change. Suppose that Northern Hemisphere temperature (this is just an example, and the same argument applies for Southern Hemisphere temperature) is below its long-run equili-

Table 2. Tests for Lag Length on the Unrestricted Vector Error Correction Model[a]

Lag	Schwartz	Hannon-Quinn	Serial Correlation	Normality
1	−8.33	−8.68	$\gamma^2(4) = 5.43$	$\chi^2(4) = 5.55$
2	−7.84	−8.41	$\gamma^2(4) = 0.31$	$\chi^2(4) = 4.48$
3	−7.34	−8.12	$\gamma^2(4) = 1.54$	$\chi^2(4) = 3.13$
4	−6.97	−7.96	$\gamma^2(4) = 6.20$	$\chi^2(4) = 2.25$
5	−6.57	−7.77	$\gamma^2(4) = 7.24$	$\chi^2(4) = 1.98$

[a]The best fit is indicated by the minimum value of the criterion.

brium value implied by the level of radiative forcing and/or perhaps Southern Hemisphere temperature. If the resultant disequilibrium causes Northern Hemisphere temperature to rise toward the long-run value implied by the cointegrating relation, α will be less than zero. For example, a value of −0.2 implies that 20% of the disequilibrium is eliminated annually by a change in temperature. If the relevant coefficient of α is zero, then disequilibrium in the cointegrating relation does not affect Northern Hemisphere temperature, and therefore equilibrium must be restored by a change in the other variables. A positive value for α indicates that the long-run relation between Northern Hemisphere temperature and the relevant variables is unstable.

[23] Information about causal relations among variables in the cointegrating relation can be inferred from both α and β. The presence of any two variables in one cointegrating relation indicates that they share a common stochastic trend. In the terminology of *Kaufmann and Stern* [1997], at least one of the variables "Granger causes" the other. Causes is modified by "Granger" (the econometrician who devised this notion) because if another variable drives the changes in both variables, but this variable is omitted from the model, there will appear to be a causal relation among the variables in the model. The direction of this causal relation is indicated by the coefficients of α, which identify the variable(s) in **y** that is affected by disequilibrium in the long-run relations among the variables. If a variable in **y**, y_i, is not Granger caused by any of the other variables in any of the long-run relations, the relevant coefficients in α will be zero. Under these conditions, y_i is said to be exogenous. Thus the dynamics in this model, like the dynamics in the model we used previously [*Kaufmann and Stern*, 1997], help identify causal direction in a way that a static regression cannot.

[24] Stratospheric sulfates are not included in the cointegrating relation because they are I(0) and by definition, cannot be responsible for stochastic trends in the temperature data. These variables are included in **d**. Our specification for **d** may omit other stationary determinants of temperature such as El Niño or the North Atlantic Oscillation, but the omission of these stationary variables should not bias our estimates of α and β.

5. Results for the Cointegration Model

[25] The first stage of modeling is defining the lag length of the VECM. We chose the number of lagged first differences to include in (8), which is given by $k - 1$, by comparing results generated by VECMs (equation (8)) that have 1–5 lags and are estimated over the same period, 1865–1990. (A referee requested that we also estimate the model for the post-1950 period only. We believe that such a short time series will not give reliable results. An alternative approach is to progressively extend the sample to include additional years after 1950. *Kaufmann and Stern* [1997] show that adding recent data strengthens the anthropogenic climate change signal.) The VECM's goodness of fit is evaluated using the Schwartz and Hannon-Quinn information criteria [*Hansen and Juselius*, 1995]. These statistics are based on the determinant of the VECM's residual covariance matrix with an adjustment for the number of degrees of freedom. Both statistics indicate that the shortest lag length, a single lag, is optimal (Table 2). At this lag length (and all other lag lengths), diagnostic statistics indicate that we cannot reject the null hypothesis that the unrestricted model's residuals are distributed normally and are not serially correlated (Table 2). Sections 5.1–5.8 describe a series of hypothesis tests that apply various restrictions to this model that are used to answer some fundamental questions about the role of human activity and natural variability in the instrumental temperature record.

5.1. Is There a Relation Between Temperature and Radiative Forcing?

[26] If there is a statistically meaningful relation between temperature and the radiative forcing of greenhouse gases, anthropogenic sulfur emissions, and/or solar irradiance, there will be one or more cointegrating vectors. We test for the presence and number of cointegrating vectors, which is equivalent to testing the rank of $\alpha\beta'$, using the λ_{trace} and λ_{max} statistics [*Johansen*, 1988; *Johansen and Juselius*, 1990]. The λ_{max} statistic tests the null hypothesis that the number of cointegrating vectors is r against the specific alternative of $r + 1$ cointegrating vectors. The λ_{trace} statistic tests the null hypothesis that there are r cointegrating vectors against the alternative that $r = 2$, which is the maximum number of cointegrating vectors possible in our model. We test two null hypotheses: that there are zero cointegrating relations ($r = 0$) and that there is one cointegrating relation ($r = 1$). Both of these null hypotheses are rejected strongly, and so we accept the hypothesis that there are two cointegrating vectors (Table 3).

[27] The presence of two cointegrating vectors indicates that there is a statistically meaningful relation between temperature and radiative forcing. This result implies that no significant integrated variable(s) has been omitted from the model. If we were unable to reject the null hypothesis of zero cointegrating vectors, we would conclude that either (1) temperature is not related to radiative forcing, (2) temperature is related to radiative forcing and other I(1) variables that are not included in the model, or (3) the relation between temperature and radiative forcing is highly nonlinear.

Table 3. Lambda Statistics for Choosing Rank of $\alpha\beta'$

		Test Statistics[a]		Critical Values[b]	
r[c]	p-r[d]	λ_{max}	λ_{trace}	λ_{max}	λ_{trace}
0	2	(60.80)	(108.05)	14.07	15.41
1	1	(47.25)	(47.25)	3.71	3.76

[a]Values that exceed the 0.05 threshold are in parentheses.
[b]Critical values are from *Osterwald-Lennum* [1992].
[c]This shows the number of cointegrating vectors under the null hypothesis.
[d]This shows the number of stochastic trends.

Table 4. Tests on Over-Identifying Restrictions[a]

	Cointegrating Relation 1						Cointegrating Relation 2						Likelihood
Model	NHEM	SHEM	RFGG	RFSUN	RFSOXNH	RFSOXSH	NHEM	SHEM	RFGG	RFSUN	RFSOXSH	RFSOXNH	Ratio Statistic
0	X	X	X	X	X	0	X	X	X	X	X	0	
1	X	X	0	X	0	0	X	X	0	X	0	0	$\chi^2[6] = (20.70)$
2	X	X	0	X	X	X	X	X	0	X	X	X	$\chi^2[2] = <6.21>$
3	X	X	X	X	0	X	X	X	X	X	X	0	$\chi^2[2] = (12.11)$
4	X	X	X	X	X	0	X	X	X	X	0	X	$\chi^2[2] = 2.67$
5	X	X	X	0	X	X	X	X	X	0	X	X	$\chi^2[2] = (16.16)$
6	0	X	X	X	X	X	0	X	X	X	X	X	$\chi^2[6] = (58.59)$
7	X	0	X	X	X	X	X	0	X	X	X	X	$\chi^2[6] = (46.57)$
8	X	0	X	X	X	0	X	X	X	X	X	0	$\chi^2[1] = 1.49$
9	X	X	X	X	X	0	0	X	X	X	X	0	$\chi^2[1] = (5.84)$
10	X	0	X	X	X	0	0	X	X	X	X	0	$\chi^2[2] = 6.15$
11	X	0	X	X	X	0	X	X	0	0	0	0	$\chi^2[4] = (10.87)$
12	X	0	X	X	X	0	X	X	0	X	0	0	$\chi^2[3] = (9.66)$
13	X	0	X	X	X	0	X	X	X	0	0	0	$\chi^2[3] = 2.68$
14	X	0	X	X	X	0	X	X	0	0	X	0	$\chi^2[3] = 1.79$
15	X	0	X^c	X^c	X^c	0	X	X	X	X	X	0	$\chi^2[4] = 8.29$
16	X	0	X	X	X	0	X	X	X^c	X^c	X^c	0	$\chi^2[3] = 3.05$
17	X	0	X^c	X^c	X	0	X	X	X^c	X^c	X^c	0	$\chi^2[4] = 5.46$
18	X	0	X	X^c	X^c	0	X	X	X^c	X^c	X^c	0	$\chi^2[4] = 6.60$
19	X	0	X^b	X	X^b	0	X	X	X^c	X^c	X^c	0	$\chi^2[4] = 3.15$

[a] Variables present in the cointegrating relation are indicated by "X" (model 0). Excluded variables are indicated by "0". Values that exceed the 0.01 threshold are in parentheses. Values that exceed the 0.05 threshold are in angle brackets.

[b] Elements of β associated with RFGG and RFSOXNH are restricted to be equal.

[c] Restrictions on the coefficients associated with these variables have been imposed such that the coefficients of adjacent superscripted values are equal.

[28] The parameterization of the unrestricted cointegrating vectors is not unique. Therefore it is not possible to calculate the standard errors for the coefficients of β. To obtain the standard errors, a minimum of one restriction is needed on each of the two cointegrating vectors, at which point the system is said to be exactly identified. Starting from the assumption that hemispheric temperature is related to radiative forcing in that hemisphere and that surface temperature is linked across hemispheres, we specify the following exactly identified system:

$$\begin{aligned}\text{CR1}\ &\beta_{11}\text{NHEM} + \beta_{12}\text{SHEM} + \beta_{13}\text{RFGG} \\ &+ \beta_{14}\text{RFSUN} + \beta_{15}\text{RFSOXNH}\end{aligned}$$

$$\begin{aligned}\text{CR2}\ &\beta_{21}\text{NHEM} + \beta_{22}\text{SHEM} + \beta_{23}\text{RFGG} \\ &+ \beta_{24}\text{RFSUN} + \beta_{26}\text{RFSOXSH}\,.\end{aligned}$$

These restrictions are associated with a zero coefficient for RFSOXSH in CR1 and a zero coefficient for RFSOXNH in CR2 in Table 4; variables present in the cointegrating relation are indicated by a cross (model 0). To test a series of hypotheses about the relation between temperature and radiative forcing, we impose additional restrictions, which are termed over-identifying restrictions. These over-identifying restrictions are evaluated with a likelihood ratio test that is distributed as a chi-square with degrees of freedom equal to the number of over-identifying restrictions. Values of the likelihood test statistic that exceed the critical value at $P < 0.05$ indicate that the relation between temperature and radiative forcing imposed by the over-identifying restriction(s) is rejected because it is inconsistent with observations.

5.2. Is Temperature Determined by Natural Variability Alone?

[29] If natural variability is solely responsible for the stochastic trends in temperature, the radiative forcing of greenhouse gases and anthropogenic sulfur emissions will not be part of the cointegrating relation with temperature. To evaluate whether RFGG and/or RFSOXNH and RFSOXSH belong in the cointegrating relations, we test restrictions that eliminate these components of radiative forcing from both cointegrating relations. These restrictions are represented by zero coefficients associated with RFGG and/or RFSOXNH and/or RFSOXSH in models 1–4 in Table 4. Restrictions which eliminate the radiative forcing of greenhouse gases and anthropogenic sulfur emissions generate over-identified model 1, which is rejected strongly (Table 4). Tests on models 2 and 3 indicate that we cannot eliminate RFGG or RFSOXNH. However, we cannot reject a restriction that eliminates RFSOXSH (model 4). These results indicate that the radiative forcing of greenhouse gases and Northern Hemisphere anthropogenic sulfur emissions are related to temperature. This result provides direct statistical evidence for the effect of human activity on surface temperature.

5.3. Is Temperature Determined by Human Activity Alone?

[30] We can evaluate the hypothesis that temperature is related to human activity alone by testing an over-identifying restriction that eliminates RFSUN from both cointegrating relations (model 5). This model is rejected strongly (Table 4). This result indicates that hemispheric surface temperature also is related to changes in solar activity.

[31] Results for the temperature effect of the other component of natural variability, the radiative forcing of stratospheric sulfates associated with volcanic activity, are mixed. The elements of **d** associated with the radiative forcing of stratospheric sulfates in the Northern Hemisphere have a statistically significant effect on temperature in the Northern Hemisphere at $P < 0.1$. Conversely, the radiative forcing of stratospheric sulfates in the Southern Hemisphere does not have a statistically measurable ($p > 0.30$) effect on temperature in either hemisphere, regardless of the restrictions placed on the cointegrating relations.

[32] Together with results from section 5.2, the statistical results indicate that surface temperature is related to both human activity and natural variability. This result is confirmed by testing restrictions that eliminate NHEM or SHEM from both cointegrating relations. The likelihood ratio statistic indicates that we can reject strongly restrictions that eliminate either NHEM (model 6) or SHEM (model 7) from both cointegrating relations (Table 4). This result indicates that the two cointegrating relations represent cointegration among temperature and radiative forcing; the components of radiative forcing do not cointegrate among themselves.

5.4. Is Hemispheric Temperature Determined by Hemispheric Forcing Alone?

[33] The just identified model postulates that temperature in each hemisphere is determined by radiative forcing in that hemisphere and temperature in the opposite hemisphere. To test the hypothesis that hemispheric temperature is determined by forcings in that hemisphere alone, we test restrictions that eliminate SHEM in CR1 and/or NHEM in CR2. First, we test whether it is possible to specify Northern Hemisphere temperature solely as a function of radiative forcing in the Northern Hemisphere. To do so, we add one over-identifying restriction to the just identified model: we eliminate SHEM from CR1. This restriction generates over-identified model 8 (Table 4), which has a cointegrating relation that includes NHEM, RFGG, RFSOXNH, and RFSUN (CR1). This combination of variables can be interpreted as the long-run equilibrium relation between surface temperature and radiative forcing in the Northern Hemisphere. As indicated in Table 4, the restriction that eliminates SHEM from the just identified model (model 8) cannot be rejected by the likelihood ratio statistic ($\chi^2(1) = 1.49$ $P > 0.23$). This result indicates that Northern Hemisphere temperature is related to radiative forcing in the Northern Hemisphere alone.

[34] We can use a similar procedure to test whether temperature in the Southern Hemisphere can be represented solely by the radiative forcings in the Southern Hemisphere. To do so, we eliminate NHEM from CR2 in the just identified model. This restriction generates model 9, which has a cointegrating relation that includes SHEM, RFGG, RFSOXSH, and RFSUN (CR2). This combination of variables can be interpreted as the long-run equilibrium relation between surface temperature and radiative forcing in the Southern Hemisphere. As indicated in Table 4, the over-identifying restriction on CR2 is rejected strongly ($\chi^2(1) = 5.84$ $P < 0.02$). This result implies that it is not possible to represent surface temperature in the Southern Hemisphere solely as a function of radiative forcing in that hemisphere.

5.5. Are Hemispheric Temperatures Linked?

[35] The inability to represent Southern Hemisphere temperature as a function of Southern Hemisphere forcing alone implies that surface temperature in the two hemispheres is linked. We can explicitly test the null hypothesis that Northern and Southern Hemisphere temperatures are independent by eliminating NHEM from CR2 in model 8. Eliminating this variable generates model 10, which specifies temperature in each of the hemispheres as a function of forcings in that hemisphere. The restriction that eliminates NHEM from CR2 in model 8 is rejected ($\chi^2(1) = 4.76$ $P < 0.03$). This rejection indicates that there is a long-run relation between temperature in the Northern and Southern Hemispheres. This is consistent with the potential for heat transfer to prevent hemispheric temperatures from drifting apart for long periods regardless of the differences in radiative forcings between the hemispheres.

5.6. How Are Hemispheric Temperatures Linked: Are They Proportional?

[36] The result that hemispheric temperatures are linked begs the nature of this linkage. The simplest linkage is linear: Temperature in one hemisphere is linearly proportional to temperature in the other. To test this hypothesis, we evaluate a set of restrictions that eliminates all of the forcing variables from CR2 in model 8. These restrictions generate model 11, which has one cointegrating relation (CR2) that includes Northern and Southern Hemisphere temperatures only (NHEM and SHEM). Restrictions that eliminate the three radiative forcing variables from CR2 in model 11 are rejected strongly ($\chi^2(3) = 9.38$, $P < 0.02$). Rejecting these restrictions indicates that Northern and Southern Hemisphere temperatures do not cointegrate; that is, temperature in the Southern Hemisphere is not linearly proportional to temperature in the Northern Hemisphere.

Table 5. Causes for Hemispheric Differences in Temperature Change[a]

Variable	NHEM Equation	SHEM Equation	Differential Effect (NHEM−SHEM)
		Model 13	
RFGG	0.58	0.45	0.13
RFSUN	1.04	0.54	0.50
RFSOXNH	0.55	0.29	0.26
RFSOXSH	...	...	...
		Model 14	
RFGG	0.58	0.32	0.26
RFSUN	1.04	0.57	0.47
RFSOXNH	0.55	0.32	0.23
RFSOXSH	...	−1.67	−1.67

[a] Values represent the hemispheric temperature effect (°C W^{-1} m^{-2}) of an increase in radiative forcing. Values are derived by solving the cointegrating relations in models 13 and 14 for mean land and sea surface temperature in the Northern Hemisphere (NHEM) and mean land and sea surface temperature in the Southern Hemisphere (SHEM).

5.7. What Forcing(s) Cause Differences in Hemispheric Temperatures?

[37] The cause(s) of hemispheric differences in temperature can be identified by evaluating models that eliminate two (instead of three, as in model 11) of the three components of radiative forcing from CR2 of model 8. Likelihood ratio statistics indicate that RFSUN does not allow NHEM and SHEM to cointegrate; restrictions that eliminate RFGG and RFSOXSH from CR2 (model 12) are rejected ($\chi^2(2) = 8.17$, $P < 0.02$). Conversely, we cannot reject restrictions that generate a cointegrating relation that eliminates RFSUN and RFSOXSH from model 8 (model 13; $\chi^2(2) = 1.19$, $P > 0.53$). Similarly, we cannot reject restrictions that eliminate RFGG and RFSUN from model 8 (model 14; $\chi^2(2) = 0.30$, $P > 0.83$).

[38] At first glance, these results seem to imply that hemispheric differences in temperature are associated with the radiative forcing of greenhouse gases or anthropogenic sulfur emissions. But this interpretation is incorrect: Models 13 and 14 indicate that hemispheric differences in temperature are associated with all components of radiative forcings. This conclusion is demonstrated by solving the cointegrating relations for NHEM and SHEM. To solve for SHEM, we substitute the cointegrating relation for Northern Hemisphere temperature (CR1) for NHEM in CR2. Each of the resulting equations indicates the hemispheric temperature effect of a 1 W m^{-2} increase in each of the sources of radiative forcing (°C W^{-1} m^{-2}). These effects are given in the first two columns in Table 5. The difference between the values in these two columns identifies the forcing(s) responsible for the different changes in hemispheric temperature over time (Table 5). That is, if the Northern Hemisphere temperature effect of RFGG (i.e., 0.58°C W^{-1} m^{-2}; model 13) is not equal to RFGG's Southern Hemisphere temperature effect (i.e., 0.45°C W^{-1} m^{-2}; model 13), a 1 W m^{-2} increase in RFGG will generate a 0.13°C long-run increase in Northern Hemisphere temperature relative to the Southern Hemisphere.

[39] As indicated by the third column in Table 5, the differences associated with each of the forcings are nonzero, which indicates that hemispheric differences in temperature are associated with all three forcings (Figure 1). Although greenhouse gases are well mixed, their greater effect in the Northern Hemisphere may be associated with hemispheric differences in the land/water ratio. Increases in solar activity also tend to increase temperature in the Northern Hemisphere relative to the Southern Hemisphere, but

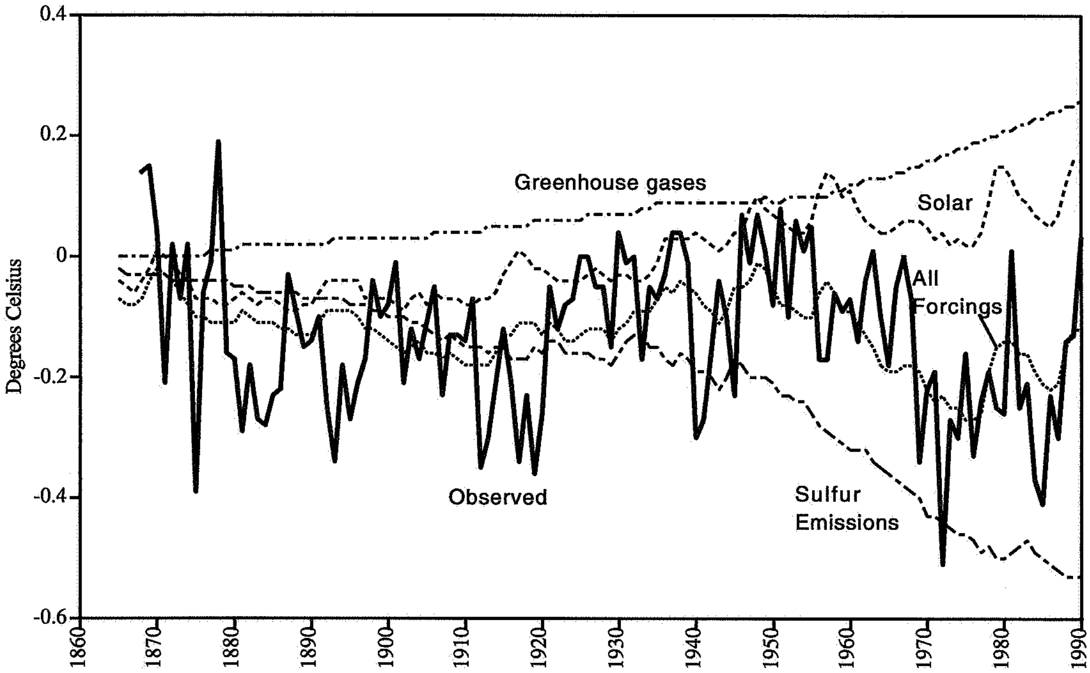

Figure 1. Causes for the difference in Northern and Southern Hemisphere surface temperatures. The observed difference in surface temperature (solid line) is associated with the radiative forcing of greenhouse gases (dash-dotted line), solar activity (dashed line), and anthropogenic sulfur emissions(dash-dotted line). Together these factors (dotted line) account for much of the difference in hemispheric temperatures; the residual from an ordinary least squares regression of the observed difference in temperature and that indicated by all three factors is stationary, as indicated by an augmented Dickey-Fuller test statistic (ADF = 5.28, $P < 0.01$). The constant from this regression is 0.207°C and represents the difference in hemispheric temperature absent the changes in human forcing and solar activity. To highlight the similarity between the observed and predicted changes in hemispheric temperature differences, the observed difference in hemispheric temperature is reduced by 0.207°C so that the mean values for the two series are the same.

their effect is smaller than the effect of greenhouse gases. Finally, anthropogenic emissions of sulfur have the largest effect on hemispheric differences in temperature, reducing Northern Hemisphere temperature by ~0.53° relative to Southern Hemisphere temperature in 1990 relative to 1865. Together, the effects of greenhouse gases, solar activity, and anthropogenic sulfur emissions can account for much of the variation in the difference between Northern and Southern Hemisphere surface temperatures.

5.8. Is the Temperature Effect of Radiative Forcing Similar Across Forcing(s)?

[40] In theory, the temperature effect of radiative forcing within a hemisphere should be equal across forcings. We test this hypothesis by imposing restrictions that equalize the elements of β associated with radiative forcing within each hemisphere. These restrictions are identified by footnotes a and b in the columns associated with radiative forcing in Table 4. The restrictions are imposed on model 8 because it represents the forcings in each hemisphere. Consistent with the conclusion that differences in hemispheric temperatures are associated with all components of radiative forcing, we do not test whether the temperature effects of individual forcing are similar across hemispheres.

[41] We reject restrictions that equalize the Northern Hemisphere temperature effect of RFGG, RFSOXNH, and RFSUN in CR1 (model 15) relative to model 8 ($\chi^2(2) = 6.8$, $P < 0.04$). However, we cannot reject restrictions that equalize the Southern Hemisphere temperature effect of RFGG, RFSUN, and RFSOXSH in CR2 (model 16) relative to model 8 ($\chi^2(2) = 1.56$, $P < 0.45$). We can impose further restrictions on model 16 to identify the components of Northern Hemisphere radiative forcing that are not equal. Relative to model 16, we just fail to reject restrictions that equalize the temperature effect of RFGG and RFSUN (model 17; $\chi^2(1) = 2.41$, $P > 0.12$). This near rejection is associated with the radiative forcing of solar activity. A restriction that equalizes the temperature effect of RFSOXNH with RFSUN (model 18) is rejected relative to model 16 at the 10% level ($\chi^2(1) = 3.55$, $P > 0.06$). However, we cannot reject a restriction ($\chi^2(1) = 0.10$, $P > 0.76$) that equalizes the temperature effect of RFGG and RFSOXNH relative to model 16. On the basis of the totality of results described in Table 4, we chose model 19 as the most parsimonious model of the relation between hemispheric temperature and radiative forcing.

6. Discussion

[42] The results in Table 6 are consistent with some basic hypotheses regarding the effect of changes in radiative forcing on temperature and offer several lines of evidence that human activity is partially responsible for the increase in temperature over the last 130 years. In all models the coefficients of β associated with radiative forcing are statistically significant and are negative. The negative sign indicates that an increase in radiative forcing is associated with an increase in temperature.

[43] The elements of β quantify the long-run relation between surface temperature and radiative forcing. When the cointegrating relations are solved for NHEM and SHEM, the elements of β can be used to calculate the long-run change in temperature that is associated with a doubling in radiative forcing (ΔT_{2X}). The size of ΔT_{2X} calculated from the elements of β falls in the middle of the range of temperature sensitivities implied by general circulation models [*Dickinson*, 1985] and statistically feasible parameterizations of energy balance climate models

Table 6. Long-Run Parameter Estimates and Diagnostic Statistics[a]

Variable	Model 0 CV1	Model 0 CV2	Model 17 CV1	Model 17 CV2	Model 18 CV1	Model 18 CV2	Model 19 CV1	Model 19 CV2
NHEM	1.000	(−0.606)(11.01)[b]	1.000	(−0.453) (5.66)[b]	1.000	(−0.460) (5.75)[b]	1.00	(−0.437) (5.46)[b]
SHEM	(−0.833) (10.5)[b]	1.000	–	1.000	–	1.000	–	1.000
RFGG	(−0.208) (1.98)[b]	−0.035 0.42[b]	(−0.760) (6.50)[b]	(−0.148) (4.23)[b]	(−0.810) (6.98)[b]	(−0.146) (4.17)[b]	(−0.542) (3.59)[b]	(−0.151) (4.31)[b]
RFSOXNH	(−0.321) (3.82)[b]	–	(−0.662) (4.94)[b]	–	(−0.709) (5.45)[b]	–	(−0.542) (3.59)[b]	–
RFSOXSH	–	1.434 1.74[b]		(−0.148) (4.23)[b]	–	(−0.146) (4.17)[b]	–	(−0.151) (4.31)[b]
RFSUN	(−5.85) (3.16)[b]	0.120 0.70[b]	(−0.760) (6.50)[b]	(−0.148) (4.23)[b]	(−0.709) (5.45)[b]	(−0.146) (4.17)[b]	(−1.110) (7.33)[b]	(−0.151) (4.31)[b]
α NHEM equation	(−1.307) (8.07)[b]	(−0.873) 4.42[b]	(−0.660) (8.40)[b]	0.198 1.67[b]	(−0.648) (8.28)[b]	0.196 1.66[b]	(−0.668) (8.66)[b]	(0.238) (2.03)[b]
α SHEM equation	(−0.862) (6.61)[b]	(−1.254) (7.88)[b]	−0.324(5.12)[b]	(−0.522) (5.50)[b]	−0.323 (5.14)[b]	(−0.523) 5.50[b]	−0.313 (5.00)[b]	(−0.503) (5.29)[b]

	Model 0	Model 17	Model 18	Model 19
Normality	$\chi^2(4)= 5.55$	$\chi^2(4)= 6.47$	$\chi^2(4)= 6.50$	$\chi^2(4)= 6.22$
Serial Correlation	$\chi^2(4)= 5.43$	$\chi^2(4)= 6.37$	$\chi^2(4)= 6.60$	$\chi^2(4)= 4.46$
Over-Identifying Restriction		$\chi^2(4)= 5.46$	$\chi^2(4)= 6.60$	$\chi^2(4)= 3.15$

[a] Values that exceed the 0.05 threshold are in parentheses.
[b] These are *t* statistics.

[*Wigley et al.*, 1997]. Doubling the preindustrial concentration of carbon dioxide increases RFGG by 4.3 W m^{-2}. This increase raises the long-run equilibrium temperature in the Northern Hemisphere by 3.3°C, 3.5°C, and 2.3°C for models 17, 18, and 19, respectively. For the same models the corresponding temperature sensitivities for the Southern Hemisphere are 2.1°C, 2.2°C, and 1.7°C.

[44] We can use the historical changes in radiative forcing, along with the long- and short-run dynamics estimated by the VECM, to quantify the changes in historical temperature that are associated with human activity as opposed to natural variability. If we hold the radiative forcing of greenhouse gases and anthropogenic sulfur emissions at their preindustrial level, model 19 implies that changes in solar irradiance and volcanic activity increase temperature in the Southern Hemisphere by ~0.29°C between 1865 and 1990, which is about half of the observed increase (Figure 2).

[45] After 1920, Southern Hemisphere temperature increases more rapidly than is simulated by natural variability alone. This difference is associated with the radiative forcing of greenhouse gases and tropospheric sulfates. If we use model 19 to calculate the change in temperature when RFGG varies as indicated by historical data (and eliminate the effects of the other forcings), the calculated increase in temperature is greater than the observed increase (Figure 2). Conversely, the temperature effect of anthropogenic sulfur emissions (both in the Northern and Southern Hemispheres) reduces temperature well below observed values. On net, the effect of greenhouse gases predominates, and this increase allows the temperature forecast generated by both human activity and natural variability to reproduce Southern Hemisphere temperature accurately (Figure 2).

[46] The combination of human activity and natural variability also can be used to reproduce Northern Hemisphere temperatures (Figure 3). However, compared to the Southern Hemisphere, the role of human and natural forcings differs. For much of the sample period the temperature increases associated with natural variability tend to overstate the observed temperature. This tendency is alleviated by including the effect of human activity. On net, human activity tends to cool temperatures in the Northern Hemisphere because the cooling effect of anthropogenic sulfur emissions tends to be larger (in an absolute sense) than the warming effect of greenhouse gases.

[47] The coefficients of α measure the rate at which temperature adjusts to changes in radiative forcing. The statistically significant coefficients of á imply that 40–50% of the disequilibrium in the long-run relation between temperature and radiative forcing is eliminated each year. This rate of adjustment probably is too large (that is, it implies rates of ocean mixing faster than indicated by physical models). Our estimated temperature sensitivities are at the middle and lower end of the range generated by global climate models. This suggests that the true temperature sensitivities are higher and that our estimates of α and β are biased in opposite directions. Future research may reduce this bias by using information generated by climate models. These models could be used to simulate the effect of oceanic and atmospheric circulation on the rate at which surface temperature adjusts to radiative forcing. These estimates could be used to restrict the elements of α and reestimate the VECM.

7. Conclusion

[48] The results of the cointegration analysis indicate that the stochastic trends in the radiative forcing of CO_2, CH_4, CFC11, CFC12, N_2O, anthropogenic sulfur emissions, and solar activity also are present in the historical data for hemispheric surface temperatures. The presence of cointegration indicates that the temperature data do not contain any significant stochastic trends that are not also present in the other variables that we have included in our model. This implies that the increase in global

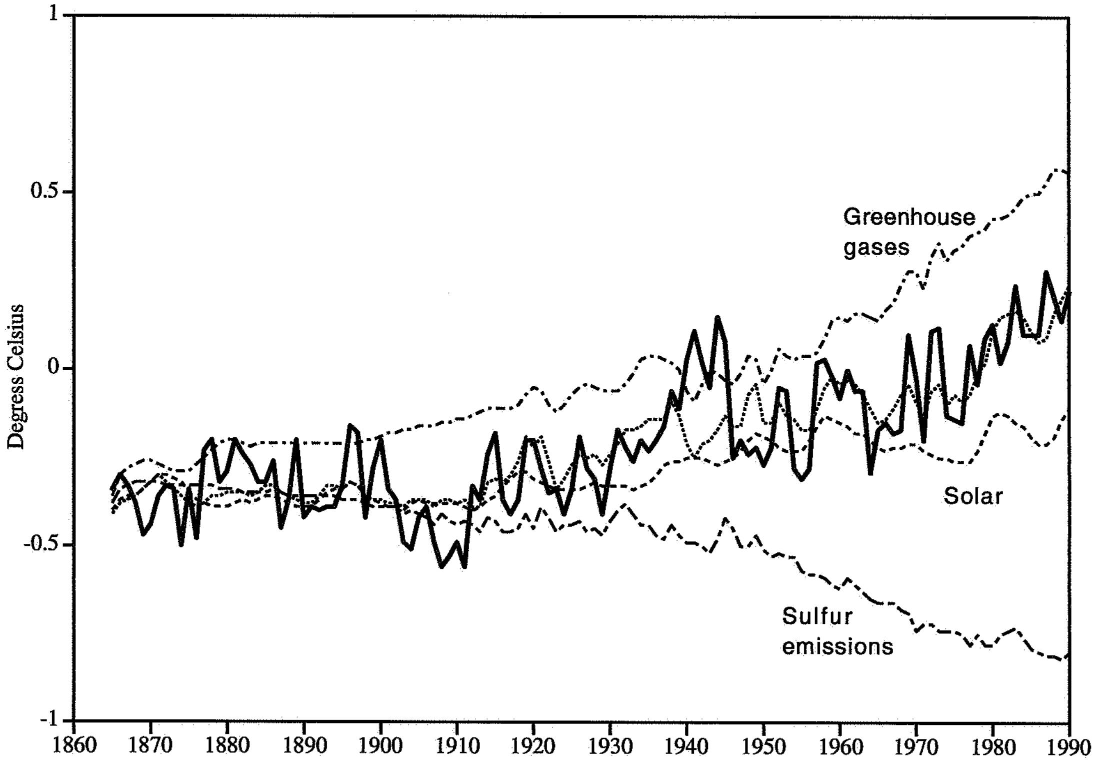

Figure 2. Decomposition of temperature changes in the Southern Hemisphere. The observed change in Southern Hemisphere surface temperature (solid line) is associated with the radiative forcing of greenhouse gases, anthropogenic sulfur emissions, and solar activity (dashed and dash-dotted lines). Together these factors (dotted line) account for much of the variation in the Southern Hemisphere temperature.

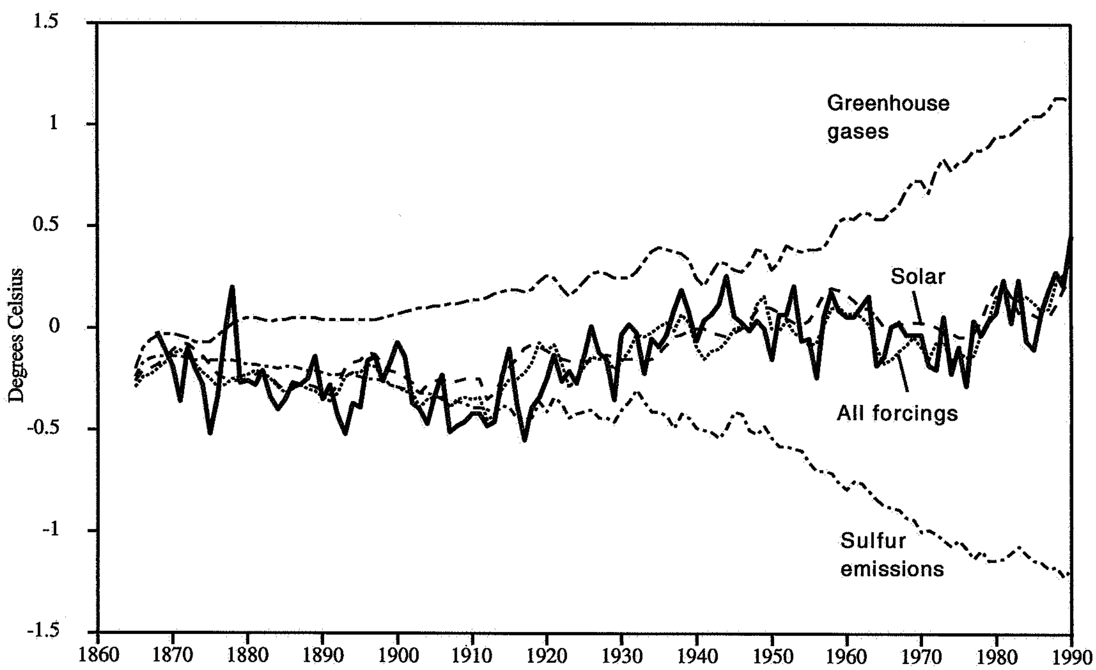

Figure 3. Decomposition of temperature changes in the Northern Hemisphere. The observed change in Northern Hemisphere surface temperature (solid line) is associated with the radiative forcing of greenhouse gases, anthropogenic sulfur emissions, and solar activity (dashed and dash-dotted lines). Together these factors (dotted line) account for much of the variation in the Northern Hemisphere temperature.

temperatures during the past 130 years can be attributed to changes in radiative forcing associated with natural variability and human activity. These results provide more support for the conclusion that [*Santer et al.*, 1996a, 1996b, p. 412] "the observed trend in global mean temperature over the past 100 years is unlikely to be entirely natural in origin."

[49] Important caveats are that the Johansen procedure assumes that the highest order of integration in the data is 1 while the radiative forcing of greenhouse gases may contain an I(2) trend and that this simple model ignores potential feedbacks between temperature and the atmospheric concentration of trace gases such as carbon dioxide and methane. Other research efforts will use structural time series techniques developed by *Harvey* [1989] to identify I(1) and I(2) trends in the historical temperature data and will use the techniques developed by *Stock and Watson* [1993] to estimate statistically meaningful relations among data for temperature, emissions, and concentrations that may contain an I(2) trend.

References

Akaike, H., Information theory and an extension of the maximum likelihood principle, in *Second International Symposium on Information Theory*, edited by P. N. Petrov, and F. Csaki, pp. 267–281, Akademiai Kiado, Budapest, 1973.

Bloomfield, P., and D. Nychka, Climate spectra and detecting climate change, *Clim. Change*, *21*, 275–287, 1992.

Cowley, T. J., Causes of climate change over the past 1000 years, *Science*, *289*, 270–277, 2000.

Dickey, D. A., and W. A. Fuller, Distribution of the estimators for autoregressive time series with a unit root, *J. Am. Stat. Assoc.*, *74*, 427–431, 1979.

Dickinson, R. E., Climate sensitivity, *Adv. Geophys.*, *28A*, 99–129, 1985.

Engle, R. E., and C. W. J. Granger, Cointegration and error-correction: Representation, estimation, and testing, *Econometrica*, *55*, 251–276, 1987.

Folland, C. K., T. R. Karl, N. Nicholls, B. S. Nyenzi, D. E. Parker, and K. Y. Vinnikov, Observed climate variability and change, in *Climate Change 1992: The Supplementary Report to the IPCC Scientific Assessment*, edited by J. T. Houghton, B. A. Callander, and S. K. Varney, pp. 135–170, Cambridge Univ. Press, New York, 1992.

Granger, C. W. J., and P. Newbold, Spurious regressions in econometrics, *J. Econometrics*, *2*, 111–120, 1974.

Hansen, H., and K. Juselius, *CATS in RATS: Cointegration Analysis of Time Series*, Estima, Evanston, Ill., 1995.

Harvey, A. C., *Forecasting, Structural Time Series Models, and the Kalman Filter*, Cambridge Univ. Press, New York, 1989.

Johansen, S., Statistical analysis of cointegration vectors, *J. Econ. Dyn. Control*, *12*, 231–254, 1988.

Johansen, S., and K. Juselius, Maximum likelihood estimation and inference on cointegration with application to the demand for money, *Oxford Bull. Econ. Stat.*, *52*, 169–209, 1990.

Johansen, S., and K. Juselius, Identification of the long run and the short run structure: An application to the ISLM model, *J. Econometrics*, *63*, 7–36, 1994.

Kaufmann, R. K., and D. I. Stern, Evidence for human influence on climate from hemispheric temperature relations, *Nature*, *388*, 39–44, 1997.

Kuo, C., C. Lindberg, and D. J. Thomson, Coherence established between atmospheric carbon dioxide and global temperature, *Nature*, *343*, 709–714, 1990.

Mitchell, J. F. B., T. C. Johns, J. M. Gregory, and S. F. B. Tett, Climate response to increasing levels of greenhouse gases and sulfate aerosols, *Nature*, *376*, 501–504, 1995.

Moore, B., and R. K. Kaufmann, The carbon cycle and the carbon dioxide problem, in *Global Climate Change: Implications, Challenges, and Mitigation Measure*, edited by S. K. Mjumdar et al., pp. 117–144, Pa. Acad. of Sci., Easton, Pa., 1992.

Osterwald-Lennum, M., A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics, *Oxford Bull. Econ. Stat.*, *54*, 461–471, 1992.

Phillips, P. C. B., Understanding spurious regressions in econometrics, *J. Econometrics*, *33*, 311–340, 1986.

Santer, B. D., T. M. L. Wigley, T. P. Barnett, and E. Anyamba, Detection of climate change and attribution of causes, in *Climate Change 1995: The Science of Climate Change*, edited by J. T. Houghton et al., pp. 407–443, Cambridge Univ. Press, New York, 1996a.

Santer, B. D., et al., A search for human influences on the thermal structure of the atmosphere, *Nature*, *382*, 39–46, 1996b.

Stern, D. I., and R. K. Kaufmann, Econometric analysis of global climate change, *Environ. Modell. Software*, *14*, 597–605, 1999.

Stern, D. I., and R. K. Kaufmann, Detecting a global warming signal in hemispheric temperature series: A structural time series analysis, *Clim. Change*, *47*, 411–438, 2000.

Stock, J. H., and M. W. Watson, A simple estimator of cointegrating vectors in higher order integrated systems, *Econometrica*, *61*, 783–820, 1993.

Tett, S. M. F. B., P. A. Stott, M. R. Allen, W. J. Ingram, and J. F. B. Mitchell, Causes of twentieth-century temperature change near the Earth's surface, *Nature*, *399*, 569–572, 1999.

Tol, R. S. J., Greenhouse statistics — Time series analysis, II, *Theor. Appl. Climatol.*, *49*, 91–102, 1994.

Tol, R. S. J., and A. F. de Vos, Greenhouse statistics — Time series analysis, *Theor. Appl. Climatol.*, *48*, 63–74, 1993.

Wigley, T. M. L., P. D. Jones, and S. C. B. Raper, The observed global warming record: What does it tell us?, *Proc. Natl. Acad. Sci.*, *94*, 8314–8320, 1997.

Wigley, T. M. L., R. L. Smith, and B. D. Santer, Anthropogenic influence on the autocorrelation structure of hemispheric mean temperatures, *Science*, *282*, 1676–1678, 1998.

Woodward, W. A., and H. L. Gray, Selecting a model for detecting the presence of a trend, *J. Clim.*, *8*, 1929–1937, 1995.

R. K. Kaufmann, Center for Energy and Environmental Studies, Boston University, 675 Commonwealth Avenue, Boston, MA 02215, USA. (kaufmann@bu.edu)

D. I. Stern, Centre for Resource and Environmental Studies, Australian National University, Canberra, ACT 0200, Australia. (dstern@cres.anu.edu.au)