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Does temperature contain a stochastic trend? Evaluating conflicting statistical results

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Abstract We evaluate the claim by Gay et al. (Clim Change 94:333–349, 2009) that "surface temperature can be better described as a trend stationary process with a one-time permanent shock" than efforts by Kaufmann et al. (Clim Change 77:249–278, 2006) to model surface temperature as a time series that contains a stochastic trend that is imparted by the time series for radiative forcing. We test this claim by comparing the in-sample forecast generated by the trend stationary model with a one-time permanent shock to the in-sample forecast generated by a cointegration/error correction model that is assumed to be stable over the 1870–2000 sample period. Results indicate that the in-sample forecast generated by the cointegration/error correction model is more accurate than the in-sample forecast generated by the trend stationary model with a one-time permanent shock. Furthermore, Monte Carlo simulations of the cointegration/error correction model generate time series for temperature that are consistent with the trend-stationary-with-a-break result generated by Gay et al. (Clim Change 94:333–349, 2009), while the time series for radiative forcing cannot be modeled as trend stationary with a one-time shock. Based on these results, we argue that modeling surface temperature as a time series that shares a stochastic trend with radiative forcing offers the possibility of greater insights regarding the potential causes of climate change and efforts to slow its progression.

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1 Introduction

The choice of statistical methodologies used to test the hypothesis that humans are (partially) responsible for changes in temperature during the instrumental record depends on the answer to the following question: are the time series for surface temperature stationary around a deterministic trend or do they contain a stochastic trend? Efforts to answer this question start with Bloomfield and Nychka (1992), which appears in *Climatic Change*. A review of this and subsequent papers indicates that conclusions about the presence/absence of a stochastic trend, which are generated by univariate statistics, depend on the test statistic and sample period (Bloomfield and Nychka 1992; Woodward and Gray 1993, 1995; Stern and Kaufmann 2000). The augmented Dickey Fuller statistic (Dickey and Fuller 1979) and the test statistic developed by Kwiatkowski et al. (1992) indicate that the time series for Northern Hemisphere, Southern Hemisphere, and global temperature contain a stochastic trend (Stern and Kaufmann 2000). The opposite result is generated by test statistics developed by Phillips and Perron (1988) and Schmidt and Phillips (1992) (Stern and Kaufmann 2000).

One way to reconcile these conflicting results is to examine the relationship between surface temperature and the factors hypothesized to cause changes in temperature, which include the radiative forcing of greenhouse gases, aerosols, and solar insolation. These forcing variables contain a stochastic trend, as indicated by all of the univariate test statistics described above (Stern and Kaufmann 2000). If the stochastic trends in the time series for radiative forcing also are present the time series for temperature, there will be a linear combination of temperature and radiative forcing that is stationary, which is termed a cointegrating relationship. Multivariate tests indicate the time series for the radiative forcing of greenhouse gases, sulfur emissions, and solar insolation cointegrate with temperature (Kaufmann et al. 2006; Kaufmann and Stern 2002). Cointegration indicates that the temperature time series contains the stochastic trend that is present in radiative forcing.

The hypothesis that surface temperature contains a stochastic trend, which it shares with radiative forcing, is challenged by Gay et al. (2009). They argue that the contradictory results about the time series properties of temperature, which are generated by univariate test statistics can be reconciled by modeling surface temperature as a trend stationary time series that contains a one-time permanent shock. That is, temperature rises linearly with time at two rates, with the change in rate defined by a one-time permanent shock. For each segment of the rise, differences between observed temperature and that implied by the linear increase are white noise. To test the null hypothesis that surface temperature is a pure random walk consisting of pure temperature variability against the alternative of a trend-stationary process with a structural change produced by an external forcing factor that has changed the long-run pattern of temperature, Gay et al. (2009) use test statistics developed by Perron (1997) and Kim and Perron (2007). Results for both test statistics reject the null hypothesis (Gay et al. 2009), which is consistent with the hypothesis that the three time series for temperature are trend stationary with a one-time permanent shock. Based on this result, Gay et al. (2009) argue "Cointegration, statistical tests and inferences that are constructed assuming that temperatures are unit root processes are not reliable."

Here we test the argument made by Gay et al. (2009) that statistical models of a cointegrating relationship between surface temperature and radiative forcing "are not reliable" and that "surface temperature can be better described as a trend stationary process with a one-time permanent shock" by comparing in-sample forecasts generated by the two models. Results indicate that the in-sample temperature forecast generated by a cointegrating relationship between temperature and radiative forcing is more accurate than the in-sample forecast generated by a trend stationary model with a one-time permanent shock. Furthermore, temperature data generated by Monte Carlo simulations of the cointegration/error correction model generate the same trend-stationary-with-a-break result described by Gay et al. (2009). Conversely, it is not possible to represent the time series for radiative forcing as a trend stationary process with a one-time permanent shock. Based on these results, we conclude that statistical models of surface temperature that are based on the notion of cointegration are superior because they can be used to test hypotheses about the physical mechanisms by which anthropogenic emissions of greenhouse gases and sulfur affect climate in ways that a trend stationary model with a one-time permanent shock cannot.

2 Materials and methods

We generate in-sample forecasts for global temperature, Northern Hemisphere temperature, and Southern Hemisphere temperature between 1870 and 2000. The start date 1870 is that used by Gay et al. (2009) and 2000 is the most recent year for which a full set of observations for radiative forcing are available (Stern 2005). The in-sample comparison is dictated by the methodology used to choose the break points for the trend stationary model, which recursively tests every possible break-point in the sample period.

The in-sample temperature forecast generated by the trend stationary model with a one-time permanent shock, which we term the trend stationary shock (TSS) model, is created by using ordinary least squares to estimate Eq. 1:

$$T_t = \alpha_1 + \pi \text{Year}_t + \delta(\text{Year}_t - \text{Year}_{\text{Breakpoint}}) + \mu_{t1} \quad (1)$$

in which T is temperature (global, Northern Hemisphere, or Southern Hemisphere) at time t (Jones et al. 2006), Year is the calendar year (e.g. 1960), $\text{Year}_{\text{Breakpoint}}$ is the year in which the break point occurs (Global 1977, Northern Hemisphere 1985, Southern Hemisphere 1911) as reported in Table 1 of Gay et al. (2009), α, π, and δ are regression coefficients that are estimated using ordinary least squares, and μ is the regression error (Table 1).

To generate the in-sample temperature forecast using the cointegration/error correction model, which we term the cointegration error correction (CEC) model, we

Table 1 Regression parameters for the trend stationary and cointegration/error correction model

	π (Eq. 1)	δ (Eq. 1)	β (Eq. 3)	ρ (Eq. 2)
Global temperature	3.57E-03[a]	1.44E-02[a]	5.00E-01[a]	−6.13E-01[a]
Northern Hemisphere	3.66E-03[a]	2.29E-02[a]	4.94E-01[a]	−5.97E-01[a]
Southern Hemisphere (full SOX)	−1.43E-03[b]	8.24E-03[a]	5.06E-01[a]	−4.60E-01[a]
Southern Hemisphere (30% of SOX)	−1.43E-03[b]	8.24E-03[a]	3.23E-01[a]	−5.35E-01[a]

[a] Coefficients are statistically significantly different from zero at the 1% level
[b] Coefficients are statistically significantly different from zero at the 10% level

update the data used by Kaufmann et al. (2006) with data from Stern (2005) through 2000. The CEC model is estimated using the methodology described by Kaufmann et al. (2006). To summarize, we estimate Eq. 2:

$$\Delta T_t = \alpha_2 + \rho\, \eta_{t-1} + \sum_{i=1}^{s} \delta_i \Delta T_{t-i} + \sum_{i=1}^{s} \phi_i \Delta F_{t-i} + \xi_t \tag{2}$$

in which F is radiative forcing, which includes the forcing (W/m^2) due to carbon dioxide, methane, CFC11, CFC12, nitrous oxide, sulfur emissions, and solar activity, Δ is the first difference operator (e.g. $\Delta F_t = F_t - F_{t-1}$) and η_t is the difference between temperature and radiative forcing in the cointegrating relationship [$\eta_t = T_t - (\alpha_1 - \beta F_t)$]. This cointegrating relationship is estimated from Eq. 3:

$$T_t = \alpha_1 + \beta F_t + \sum_{i=-s}^{k} \theta_i \Delta F_{t-i} + \mu_t \tag{3}$$

using dynamic ordinary least squares (DOLS) as described by Kaufmann et al. (2006). Unlike Kaufmann et al. (2006), the error correction model (Eq. 2) does not include stationary variables such as El Nino events and volcanic eruptions (Table 1) to ensure a fair comparison with the TSS model, which is designed to simulate the long-run increase in temperature, and not stationary variations around the deterministic trend.

The CEC in-sample temperature forecast ($\hat{T}_{tCEC}$) is generated by simulating Eq. 4:

$$\hat{T}_{tCEC} = \hat{T}_{t-1CEC} + \rho\big(\hat{T}_{t-1CEC} - (\alpha_1 + \beta F_{t-1})\big) + \alpha_2 + \sum_{i=1}^{s} \delta_i \Delta \hat{T}_{t-iCEC} + \sum_{i=1}^{s} \phi_i \Delta F_{t-i} \tag{4}$$

iteratively over the 1870–2000 sample period using the regression coefficients estimated from Eqs. 2 and 3 and the observed value for temperature in 1869 to start the simulation.

Both in-sample forecasts appear to fit observed temperature fairly well (Fig. 1a–c). Part of this consistency is associated with the in-sample nature of the forecast. That is, both models are fit to the entire set of data available. We assess the ability of the TSS and CEC models to simulate surface temperature in-sample using the following loss function:

$$d_t = \left[T_t - \hat{T}_{tCEC}\right]^2 - \left[T_t - \hat{T}_{tTSS}\right]^2 \tag{5}$$

in which $\hat{T}_{tTSS}$ is the in-sample temperature forecast generated by the TSS model (Eq. 1). Values of d_t are used to calculate the S_2a test statistic (Lehmann 1975) as follows:

$$S_{2a} = \frac{\sum_{t=1}^{N} I_+(d_t) - 0.5N}{\sqrt{0.25N}} \tag{6}$$

$$I_+(d_t) = 1 \qquad if\ d_t > 0$$
$$= 0\ otherwise$$

in which N is the number of observations.

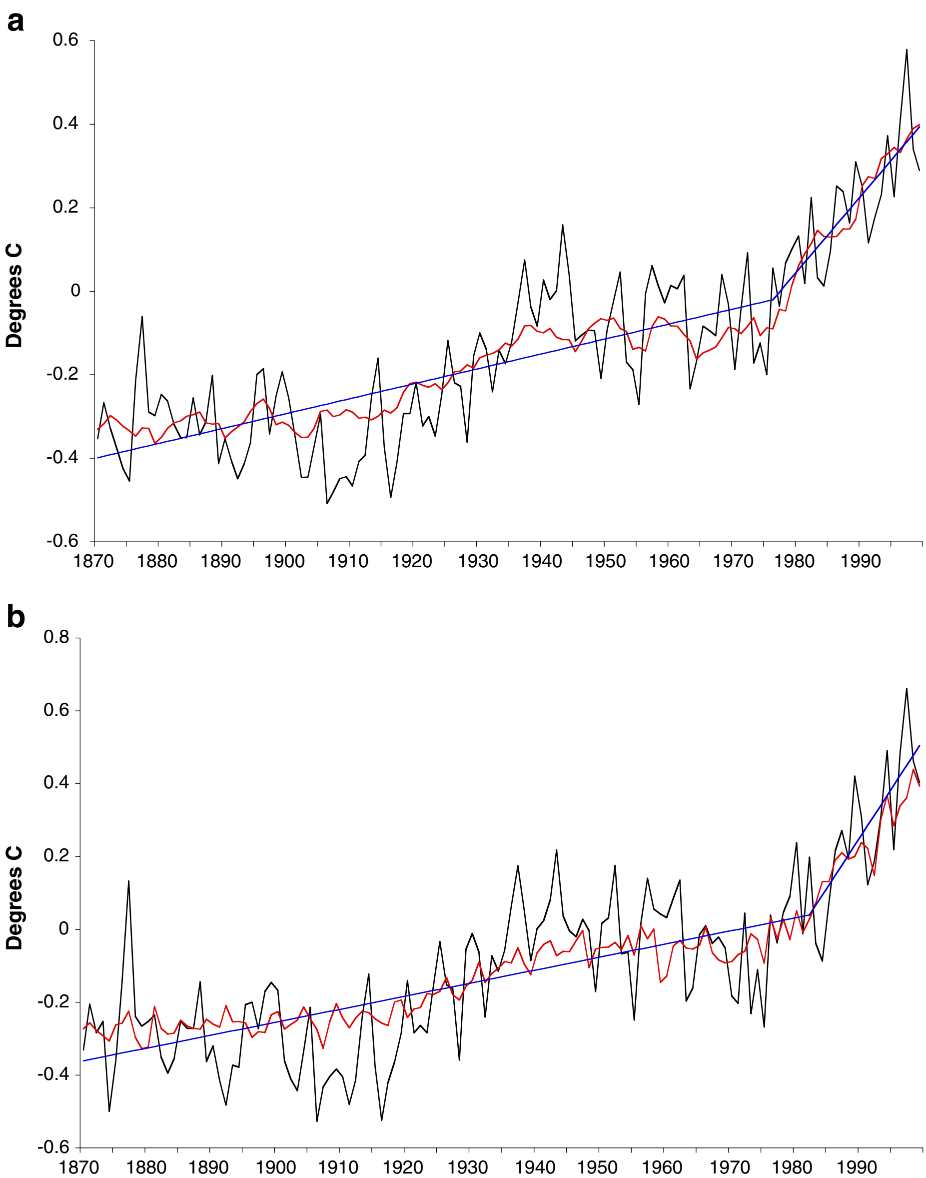

Fig. 1 **a** Observed values for global surface temperature (*black line*) and the in-sample temperature forecast generated by the CEC model (*red line*) and the TSS model (*blue line*). **b** Same as **a** for Northern Hemisphere temperature **c** Same as **a** but for Southern Hemisphere temperature

The S_{2a} statistic tests the null hypothesis that the in-sample temperature forecasts simulated by the CEC and TSS models are equally accurate and is asymptotically standard normal under the null. A negative value for the S_{2a} statistic that exceeds the $p = .05$ threshold (-1.96) indicates that the in-sample temperature forecast generated by the CEC model is closer to the observed value of temperature than

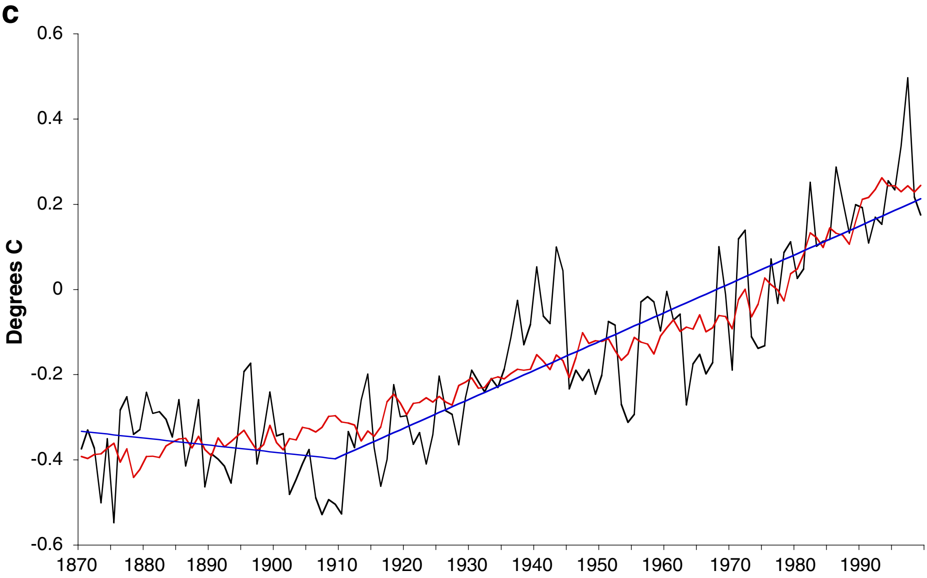

Fig. 1 (continued)

the in-sample temperature forecast generated by the TSS model more often than expected by random chance. Under these conditions, we would conclude that the CEC model generates a more accurate in-sample temperature forecast than the TSS model.

To evaluate the degree to which this conclusion is robust, we also use a statistic developed by Diebold and Mariano (1995).[1] This test can be summarized as a t-test on the statistical significance of the constant (α) in the following regression:

$$d_t = \alpha + \mu_t \tag{7}$$

in which a non-zero value of α (as measured against a non-standard asymptotic distribution) indicates that the accuracy of the two in-sample temperature simulations can be distinguished statistically. Again, a negative value for α that exceeds the critical threshold would indicate that the CEC model generates a more accurate in-sample temperature forecast than the TSS model.

3 Results

Both statistical tests indicate that the in-sample forecast for global and Northern Hemisphere temperature generated by the CEC model is more accurate than the TSS model. For both of the in-sample temperature forecasts, the S_{2a} statistic is negative and indicates that the in-sample temperature forecast generated by the CEC model is closer to the observed value than the in-sample temperature forecast generated by

[1] We recognize that this statistic is designed for out-of-sample forecasts, but we use it to evaluate the degree to which results generated by the parametric test given by Eq. 6 are robust.

Table 2 Results of model comparisons

Temperature series	S_2a	Diebold & Mariano
Global	-2.28^a	-3.35^b
Northern Hemisphere	-3.14^b	-3.15^b
Southern Hemisphere (full SOX)	2.28^a	0.78
Southern Hemisphere (30% of SOX)	0.35	-0.24

[a]Coefficients are statistically significantly different from zero at the 5% level
[b]Coefficients are statistically significantly different from zero at the 1% level

the TSS model more often than expected by random chance ($p < .05$) (Table 2). This result is confirmed by the test statistic developed by Diebold and Mariano (1995), which indicates we can reject the null hypothesis that the accuracy of the CEC model's in-sample temperature forecast is equal to the accuracy of the TSS model's in-sample temperature forecast versus the alternative hypothesis that the CEC model's in-sample temperature forecast is more accurate than the TSS model's in-sample temperature forecast (Table 2).

Comparisons of the in-sample temperature forecast for Southern Hemisphere temperature generate mixed results. The S_{2a} statistic is positive and statistically significant at the 5% level, which indicates that the in-sample temperature forecast generated by the TSS model is closer to the observed value more often than the in-sample temperature forecast generated by the CEC model On the other hand, the test statistic developed by Diebold and Mariano (1995) indicates that we cannot reject the null hypothesis that the accuracy of the CEC model's in-sample temperature forecast is equal to the accuracy of the TSS model's in-sample temperature forecast versus the alternative hypothesis that the accuracy of the TSS model's in-sample temperature forecast is more accurate than the CEC model's in-sample temperature forecast (Table 2).

The relatively poor performance of the CEC model for the Southern Hemisphere may be caused by using the global value of anthropogenic sulfur emissions to estimate Eqs. 2 and 3 and to simulate Eq. 4.[2] The global value of anthropogenic sulfur emissions greatly overstates its effect in the Southern Hemisphere because most of these emissions occur in the Northern Hemisphere and have a relatively short atmospheric residence time, a week to 10 days. Consistent with this hypothesis, if we estimate and simulate the CEC model with a scaled value for anthropogenic sulfur emissions (30% of the global value), the in-sample temperature forecasts for the Southern Hemisphere generated by the CEC and TSS models are statistically indistinguishable (Table 2). Ironically, the effect of modifying anthropogenic sulfur emissions on the ability of the CEC model to forecast Southern Hemisphere temperature in-sample reinforces the notion that stochastic trends in the time series for radiative forcing also are present in the time series for surface temperature.

4 Discussion

At first glance, comparing forecasts generated by the TSS and CEC models seems 'unfair' because Eqs. 2 and 3 contain more parameters than Eq. 1. But the CEC

[2]Kaufmann et al. (2006) estimate Eqs. 2 and 3 with data for global surface temperature only.

model (Eqs. 2–3) is estimated only once because it assumes that the relationship between temperature and radiative forcing is stable over the sample period. The stability of the relationship is confirmed statistically by Mills (2009). Conversely, the TSS model allows the relationship to change during the sample period and Gay et al. (2009) identify the date of this change by estimating Eq. 1 with every possible date of change. This repeated estimation implies that the TSS model has fewer degrees of freedom than implied by the number of coefficients in Eq. 1. The distorting effect of repeated sampling on diagnostic statistics (and their degrees of freedom) is demonstrated repeatedly in the econometric literature (e.g. Christiano 1992). As such, the comparison of the in-sample temperature forecast generated by the CEC and TSS models is much 'fairer' than implied by the number of parameters in each.

The TSS and CEC models can be evaluated further by comparing their generality. That is, can the hypothesis that the time series for temperature and radiative forcing contain a stochastic trend and cointegrate account for the one-time permanent shock represented by the TSS model? To test the hypothesis that changes in the radiative forcing can account for the results generated by Gay et al. (2009), we use Monte Carlo techniques to generate one thousand experimental data sets for global surface temperature using the observed values for radiative forcing and errors of 0.111 and 0.097, which are estimated for Eqs. 2 and 3, respectively. We test whether the resultant temperature time series can be represented as trend stationary with a break using the procedure described by Perron (1997). The test statistic rejects the null hypothesis that the experimental temperature time series contains a stochastic trend for 955 of the thousand data sets. Rejecting the null hypothesis in more than 95% of the data sets indicates that the experimental temperature series can be modeled as trend stationary with a one-time permanent shock. This result implies that the historical evolution of anthropogenic forcings, which contain a stochastic trend, generates temperature data that appear to be trend stationary with a break.

Break points in deterministic trends fit to surface temperature can be explained based on observed changes in radiative forcing. As described by Kaufmann et al. (2006), radiative forcing associated with greenhouse gases rises irregularly throughout the historical record (Fig. 2). On the other hand, there is a clear slowing and reversal in anthropogenic sulfur emissions during the 1980's (Fig. 2). This 'shock' is caused by legislation that is aimed at reducing air pollution in general and acid deposition in particular. From our perspective, implementing this legislation created a shock because it reduced the cooling effects of sulfur aerosols, which increased the realized rate of warming due to on-going increases in greenhouse gases.

Alternatively, the CEC model may be able to generate temperature data that can be can be modeled as trend stationary with a one-time permanent shock if the time series for radiative forcing are trend stationary with a one-time permanent shock. To test this hypothesis, we use the test statistic developed by Perron (1997) to analyze the time series for radiative forcing. Consistent with a visual examination of the data in Fig. 2, the test statistics for total radiative forcing (−3.10), total greenhouse gases (−2.97), and anthropogenic sulfur emissions (−1.83) fail to reject (at the 5% level −4.71) the null hypothesis that the series contains a unit root (against the alternative that the series are trend stationary with a one-time permanent shock). As such, this result is inconsistent with the hypothesis that temperature and radiative

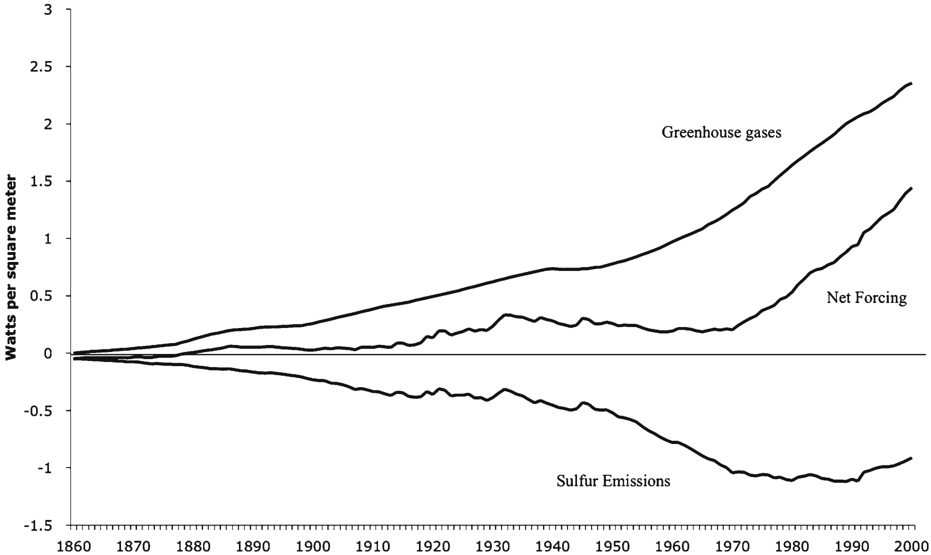

Fig. 2 The series for the readiative forcing of anthropogenic sulfur emissions (SOX), greenhouse gases (GG) and the total of all forcings that contain a stochastic trend, which includes greenhouse gases, anthropogenic sulfur emissions, and solar insolation

forcing cointegrate because radiative forcing plays the role of a broken trend in the cointegration test.[3]

The historical evolution of anthropogenic forcing also may help explain the different break-points for the Southern Hemisphere, 1911, relative to 1977 and 1985 for the global and Northern Hemisphere temperature time series, respectively. Because most anthropogenic sulfur emissions occur in the Northern Hemisphere and these emissions have a relatively short residence time in the atmosphere, radiative forcing varies between hemispheres (Kiehl and Briegleb 1993). This causes the Northern and Southern Hemispheres to warm at different rates (Kaufmann and Stern 1997, 2002; Wigley et al. 1998).

The notion that time series for surface temperature contains a stochastic trend also is consistent with the physical understanding of the climate system. Gay et al. (2009) claim "assuming a unit root implies that global and hemispheric temperatures are highly unstable processes and therefore single events such as isolated solar flares, the 1974 La Nina (as well as other internal variation) or the 1883 Krakatau eruption would have changed the long-run path of global temperatures and their effect would be present even today." This misrepresents the explanation for a stochastic trend in temperature. As explained in Kaufmann et al. (2006) "The stochastic trends in temperature are caused by the stochastic trends in the radiative forcings that drive temperature and not temperature itself. That is a direct shock to temperature does not accumulate over time." Because the forcing described by Gay et al. (2009) (e.g. solar flares, the 194 La Nina, or the 1883 Krakatau eruption) are stationary, they

[3]This hypothesis was suggested by a reviewer, who we thank for helping us to strengthen the analysis.

would not impart a stochastic trend to temperature. Indeed, the stationary effects of volcanic eruptions and El Nino events are modelled in the error correction model reported by Kaufmann et al. (2006).

Furthermore, our explanation for a stochastic trend in surface temperature can be used to reconcile the conflicting results about the time series properties of temperature that are generated by univariate test statistics. Physical models of the undisturbed climate system indicate that surface temperature is stationary with considerable natural variation. That is, temperature varies from year-to-year, but this variation does not persist—surface temperature is inherently stationary. Long-run changes in surface temperature associated with anthropogenic climate change are driven by changes in radiative forcings, which contain stochastic trends. To date, the effects of anthropogenic increases in radiative forcing on temperature are small relative to natural variability. As such, the temperature time series have a low signal to noise ratio. This low signal to noise ratio increases the likelihood that results generated by univariate test statistics, will make a type I error (Schwert 1989; Phillips and Perron 1988; Kim and Schmidt 1990). Under these conditions, univariate test statistics will mistakenly indicate that the temperature time series are trend stationary.

5 Conclusions

The adage, "there are many ways to skin a cat" is applicable to statistical models of surface temperature. Statistical models indicate that surface temperature can be simulated either as a trend stationary process with a one-time permanent shock or as having a stochastic trend. These statistical representations embody very different hypotheses about the drivers of temperature changes during the instrumental record. Gay et al. (2009) argue that modeling temperature as a deterministic trend with a single break can be explained by changes in "key external forcing factors such as Earth orbit changes, solar irradiance, and greenhouse gas concentrations that hardly occur in decadal and century time scale…occurred in 1977, 1985, and 1911 in G [global] NH, and SH respectively." Although these events are rare and sufficiently large to mark a one-time permanent change in the temperature time series, Gay et al. (2009) do not offer a single change to coincide with these dates or even why these dates would vary across hemispheres. Conversely, the notion of cointegration allows users to estimate statistical models that are based the hypothesis that changes in radiative forcing, which is influenced in part by human activity, generates changes in surface temperature during the instrumental temperature record. As such, this approach offers the possibility of greater insights regarding the causes of climate change and efforts to slow its progression.

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