Warming Break Trends and Fractional Integration in the Northern, Southern, and Global Temperature Anomaly Series

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ABSTRACT

This paper deals with the estimation of time trends in temperature anomaly series. However, instead of imposing that the estimated residuals from the time trends are covariance stationary processes with spectral density that is positive and finite at the zero frequency [$I(0)$], the author allows them to be fractionally integrated. In this context, a new procedure for testing fractional integration with segmented trends is applied to the northern, southern, and global temperature anomaly series. The results show that the three series are fractionally integrated, and the warming effects are substantially higher after the break in all cases.

1. Introduction

The main purpose of this article is to examine if there are significant trends in the global and hemispheric temperature anomaly series. Denoting a time series for temperature anomalies by y_t, the standard approach is to employ a simple linear regression model of form

$$y_t = \alpha + \beta t + u_t, \qquad t = 1, 2, \ldots, \tag{1}$$

testing the significance of the estimated slope coefficient for β in (1). It is not uncommon to find estimates of β based on ordinary least squares (OLS). However, statistical inference based on standard t or F statistics is only valid here if (1) satisfies some restrictive conditions, which are rarely satisfied in temperature time series. Thus, for example, the error term in (1) should be uncorrelated. If there is some autocorrelation in (1), the autoregressive AR(1) process

$$u_t = \rho u_{t-1} + \upsilon_t, \qquad t = 1, 2, \ldots \tag{2}$$

has been widely employed in the climatological community because of its relation with the stochastic first-order differential equation. In this case, generalized least squares (GLS) is usually adopted for the estimation of β.[1] Nevertheless, in both cases [i.e., no autocorrelation and AR(1) u_t] the series is supposed to be stationary $I(0)$ once the time trend has been removed. If the detrended series is not $I(0)$ the classic alternative is to assume that the series is nonstationarity or that it contains a unit root, also called integration of order 1 [$I(1)$], and u_t in (1) is then described as

$$u_t = u_{t-1} + \upsilon_t, \qquad t = 1, 2, \ldots,$$

where υ_t is supposed to be $I(0)$. Thus, it is crucial to determine if the error term in (1) is stationary $I(0)$ or nonstationary $I(1)$.[2,3]

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[1] In the context of autocorrelated disturbances, we can use the Prais and Winsten (1954) transformation, in order to obtain a t statistic, which converges in distribution to a $N(0, 1)$ random variable. However, as noted by Park and Mitchell (1980) and Woodward and Gray (1993), significant size distortions appear in the test statistic when the coefficient is close to 1. Canjels and Watson (1997) have proposed a conservative approach that controls these size distortions.

[2] McKitrick (2001) states the importance of analyzing the time series properties of the surface temperatures when testing for trends. He showed that inference based on naïve modeling strategies can lead to unreliable conclusions about the warming effect. See, also Zheng and Basher (1999).

[3] An $I(0)$ process is defined here as a covariance stationary process with spectral density function that is positive and finite at the zero frequency. It thus includes the standard white noise case, but also stationary AR, moving averages (MAs), stationary autoregressive moving averages (ARMAs), etc.

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The most common used indicator of climate change is the surface air temperature and there is a vast amount of papers examining the trends in global and regional mean temperatures over time (Ghil and Vautard 1991; Hasselmann 1993; Schlesinger and Ramankutty 1994; North and Kim 1995; North et al. 1995) and in global patterns of temperature change (Santer et al. 1995; Hegerl et al. 1996, 1997; Jones and Hegerl 1998, etc.). Most of these papers conclude that global mean annual surface temperatures have increased between 0.3° and 0.6°C during the last 150 yr (Hansen and Lebedeff 1988; Nicholls et al. 1996; Jones et al. 1997). In most of these articles, it is assumed $I(0)$ stationarity for u_t in (1), while unit roots are found in global surface temperature in Stern and Kaufmann (2000) and Kaufmann et al. (2006).

In this article we extend the previous literature in two aspects. First, we consider fractional degrees of integration for the disturbance term u_t in (1). This is clearly more general than the standard approaches based on $I(0)/I(1)$ specifications, also including these two approaches as particular cases of interest. Second, we permit the existence of a structural break, which is endogenously determined by the model, and this allows us to consider the case of segmented trends in the temperature series. These two issues are relevant in the analysis of the warming effect. First, to correctly determine the degree of integration of the error term is crucial for the estimation of the time trend coefficients: misspecification of the degree of dependence leads to inconsistent estimates of these coefficients. On the other hand, it is plausible to assume that the degree of persistence of the series has changed across the years, leading also to different estimates of the time trend coefficients across subsamples.

Fractionally integrated models have been employed to analyze temperature time series in previous research. Thus, for example, Gil-Alana (2005) examines the temperatures in the Northern Hemisphere from a fractional viewpoint. He uses data from 1854 to 1999. The present work goes beyond that paper in various aspects: first, it looks not only at the northern temperatures but also at global and Southern Hemisphere temperature anomalies for a time period that goes from 1850 through 2006. Moreover, including a structural break, it allows us to consider the possibility of time-varying trend coefficients along with different degrees of persistence for each subsample. The remainder of the paper is structured as follows: section 2 presents the model considered in the paper. Section 3 describes the time series data. Section 4 is devoted to the empirical work on the temperature anomaly series, while section 5 concludes the paper.

2. Fractional integration and segmented trends

For the purpose of the present work we define an $I(0)$ process as a covariance stationary process with spectral density that is positive and finite at the zero frequency. Thus, it may be a simple white noise process, but it may also include some type of weak dependence (e.g., AR) structure. When first differences are required to achieve $I(0)$, the series is said to be $I(1)$. However, the $I(0)$ and the $I(1)$ models are merely two particular cases of a much more general class of processes called fractionally integrated [$I(d)$] processes, where d [that is, the number of differences required to get $I(0)$] may be a real value. In other words, we say that u_t is $I(d)$ if

$$(1 - L)^d u_t = \upsilon_t, \qquad t = 1, 2, \ldots, \tag{3}$$

with $u_t = 0$ and $t \leq 0$, where L is the lag operator (i.e., $Lu_t = u_{t-1}$) and υ_t is $I(0)$.[4] Note that the polynomial in the left-hand side in (3) can be expressed in terms of its binomial expansion, such that, for all real d

$$(1 - L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j$$
$$= 1 - dL + \frac{d(d-1)}{2} L^2 - \ldots \tag{4}$$

and (3) can be written as

$$u_t = du_{t-1} - \frac{d(d-1)}{2} u_{t-2} + \cdots + \upsilon_t.$$

If d is an integer value, u_t will be a function of a finite number of past observations, while if d is real, u_t depends strongly upon values of the time series far away in the past (see, e.g., Granger and Ding 1996; Dueker and Asea 1995). Moreover, the higher the d is, the higher will be the level of association between the observations. Examples of this type of model in meteorological time series data are, among others, the papers of Bloomfield (1992), Smith (1993), Lewis and Ray (1997), Pethkar and Selvam (1997), Koscielny-Bunde et al. (1998), Pelletier and Turcotte (1999), Percival et al. (2004), Maraun et al. (2004), and Gil-Alana (2003, 2005).

In the first part of the empirical application carried out in the following section, we consider models of the same form as in (1)–(3), testing the significance of the slope coefficient in a model where the disturbance term

[4] The condition $u_t = 0$, $t \leq 0$ is required for the type II definition of fractional integration. For an alternative definition (type I) see Marinucci and Robinson (1999).

may be fractionally integrated. In the second part, we extend the model to allow for a segmented trend. In particular, we consider models of form

$$y_t = \alpha_1 + \beta_1 t + x_t; \quad (1 - L)^{d_1} x_t = u_t, \quad t = 1, \ldots, T_b \quad \text{and} \tag{5}$$

$$y_t = \alpha_2 + \beta_2 t + x_t; \quad (1 - L)^{d_2} x_t = u_t, \quad t = T_b + 1, \ldots, T, \tag{6}$$

where the α's and the β's are the coefficients corresponding, respectively, to the intercepts and the linear trends; d_1 and d_2 may be real values and they are the orders of integration for each subsample, u_t is $I(0)$, and T_b is the time of the break that is supposed to be unknown. Note that the model in (5) and (6) can also be written as

$$(1 - L)^{d_1} y_t = \alpha_1 \tilde{1}_t(d_1) + \beta_1 \tilde{t}_t(d_1) + u_t, \quad t = 1, \ldots, T_b, \tag{7}$$

$$(1 - L)^{d_2} y_t = \alpha_2 \tilde{1}_t(d_2) + \beta_2 \tilde{t}_t(d_2) + u_t, \quad t = T_b + 1, \ldots, T, \tag{8}$$

where $\tilde{1}_t(d_i) = (1 - L)^{d_i} 1$, $\tilde{t}_t(d_i) = (1 - L)^{d_i} t$, and $i = 1, 2$.[5]

The method presented here is based on the least squares principle. First, we choose a grid for the values of the fractionally differencing parameters d_1 and d_2, for example, $d_{io} = 0, 0.001, 0.002, \ldots, 1$, $i = 1, 2$. Then, for a given partition $\{T_b\}$ and given d_1, d_2 values (d_{1o}, d_{2o}) we estimate the α's and the β's by minimizing the sum of squared residuals,

$$\min_{\text{w.r.t.}\{\alpha_1, \alpha_2, \beta_1, \beta_2\}} \sum_{t=1}^{T_b} [(1 - L)^{d_{1o}} y_t - \alpha_1 \tilde{1}_t(d_{1o}) - \beta_1 \tilde{t}_t(d_{1o})]^2 + \sum_{t=T_b+1}^{T} [(1 - L)^{d_{2o}} y_t - \alpha_2 \tilde{1}_t(d_{2o}) - \beta_2 \tilde{t}_t(d_{2o})]^2,$$

in case of uncorrelated disturbances or use other methods like GLS with autocorrelated u_t.

Let $\hat{\alpha}[T_b; d_{1o}^{(1)}, d_{2o}^{(1)}]$ and $\hat{\beta}[T_b; d_{1o}^{(1)}, d_{2o}^{(1)}]$ denote the resulting estimates for partition $\{T_b\}$ and initial values $d_{1o}^{(1)}$ and $d_{2o}^{(1)}$. Substituting these estimated values on the objective function, we have $\text{RSS}[T_b; d_{1o}^{(1)}, d_{2o}^{(1)}]$, and minimizing this expression across all values of d_{1o} and d_{2o} in the grid we obtain $\text{RSS}(T_b) = \arg\min_{\{i,j\}} \text{RSS}[T_b; d_{1o}^{(i)}, d_{2o}^{(j)}]$. Then, the estimated break date, $\hat{T}_k$, is such that $\hat{T}_k = \arg\min_{i=1,\ldots,m} \text{RSS}(T_i)$, where the minimization is taken over all partitions $T_1, T_2, \ldots, T_m$, such that $T_i - T_{i-1} \geq |\varepsilon T|$. Then, the regression parameter estimates are the associated least squares estimates of the estimated k partition, that is, $\hat{\alpha}_i = \hat{\alpha}_i(\{\hat{T}_k\})$, $\hat{\beta}_i = \hat{\beta}_i(\{\hat{T}_k\})$, and their corresponding differencing parameters, $\hat{d}_i = \hat{d}_i(\{\hat{T}_k\})$, for $i = 1$ and 2. Several Monte Carlo results based on the model in (5) and (6) are provided in Gil-Alana (2008). In that paper the author shows that the method performs relatively well even with small samples.

The possibility of segmented trends in temperature time series has not been widely examined so far. In a recent paper, however, Wu and Zhao (2007) develop a procedure for breaks in trends in means nonstationary models and apply it to the global monthly temperatures from 1856 to 2000. They conclude there are no jumps in linear trends and suggest that a quadratic trend could be more appropriate for this dataset. This result is also in line with Rust (2003), who fitted a quadratic trend for the same dataset. Nevertheless, these authors do not consider the possibility of fractional integration, and it is now a well-known stylized fact that fractional integration and structural breaks are issues that are intimately related. Moreover, it seems reasonable for historical data as those analyzed in this paper to assume that the degree of persistence in the data (and thus, the estimation of the time trend coefficients) has changed across the years.[6]

3. The temperature anomaly series

The time series data analyzed in this paper correspond to the global and hemispheric temperature anomaly series, obtained from the Climatic Research Unit (CRU) at the University of East Anglia, United Kingdom, and are available online at http://www. cru. uea.ac.uk/cru/data/temperature. They are annual data from 1850 to 2006, and the anomalies are with respect to 1961–90. These data are continually updated and expanded by P. Jones of the CRU with help from colleagues at the CRU and other institutions. Some of the earliest work in producing these series dates back to Jones et al. (1986a,b,c), Jones (1988, 1994), and Jones and Briffa (1992). The data consist of surface air tem-

[5] Robinson and Iacone (2005) examine the interaction of long memory with deterministic trends.

[6] Diebold and Inoue (2001), Granger and Hyung (2004), and others have shown that fractional integration and structural break models can be easily confused.

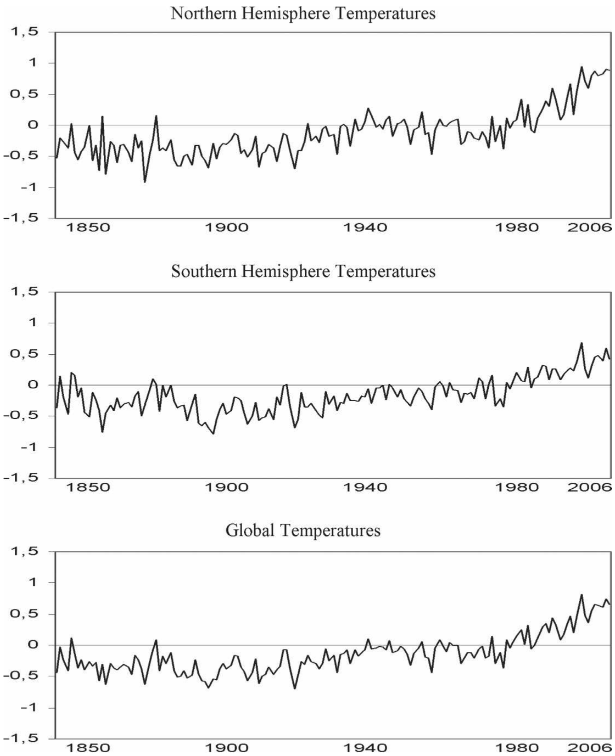

FIG. 1. Original time series. The series are anomalies with respect to 1961–90.

perature data (land surface temperature) from over 3000 station records that have been corrected for nonclimatic errors, such as station shifts and/or instrument changes (Jones 1994). Coverage is denser over the more populated parts of the world, particularly the United States, southern Canada, Europe, and Japan and is sparsest over the interior of the South American and African continents and over the Antarctic. The number of available stations was small during the 1850s but increases to over 3000 stations during the 1951–90 period. A review of the methods employed and data available can be found in Jones et al. (2006).

Figure 1 displays the plots of the three series. The northern and southern temperature series show some general similarities, for example, a little sign of trends before 1900, a peak in the early 1940s, and the highest temperatures occurring after 1980. However, according to Jones et al. (2006),

> [T]here are several notable differences between the two series: a steady period of warming is seen for the northern hemisphere from about 1910 through the mid-1940s. For the southern hemisphere there is less warming observed from 1910 through 1930, with sudden and rapid warming from 1930 through mid-1940s. The northern hemisphere records show gradual cooling from the mid-1940s through the mid-1970s, followed by rather steady temperature increases thereafter. The southern hemisphere shows an abrupt shift to cooler temperatures after 1945, quite variable temperatures until the mid-1960s, followed by a gradual increase over the remainder of the record.

For the global temperatures stable temperatures are observed from the beginning of the record through about 1910, with relatively rapid and steady warming through the early 1940s, followed by another period of relatively stable temperatures through the mid-1970s. From this point onward, another rapid rise was observed. The year 1998 was the warmest year to date, followed by 2005, and 9 of the 10 warmest years in the sample occurred in the last 10 yr (1995–2006).

Jones et al. (2006) estimated linear trends on these three series based on simple linear regression techniques, and the results showed a warming trend of about 0.69°C for the global and Northern Hemisphere temperatures and about 0.70°C for the southern temperatures anomaly series. Other studies using these and other variables for shorter time periods found values for the warming effect slightly smaller than those reported in Jones et al. (2006). Thus, for example, Gil-Alana (2005) found an estimate of about 0.48°C for the Northern Hemisphere anomalies for the time period 1854–2001. Smith (1993) applied a long memory model to warming data over a variety of sites in central England and the continental United States and estimated the temperature increases to be between 0.27° and 0.35°C. Standard errors of these estimators ranged between 0.19 and 0.31, however, suggesting a marginal but not strongly significant increase in long-range temperatures. Using global temperature averages collected by Hansen and Lebedeff (1988), Smith and Chen (1996) proposed a joint estimation of the long memory parameter and the time trend and found an estimate for the time trend of about 0.55°C.

4. Empirical results on the temperature anomaly series

First, we suppose that there are no breaks in the data and thus, we consider a model of the form as in (1) and (3), testing the null hypothesis

$$H_o{:}d = d_o \tag{9}$$

for any real value d_o. Thus, under H_o (9) the model becomes

$$y_t = \alpha + \beta t + u_t, \qquad t = 1, 2, \ldots, \quad \text{and} \tag{10}$$

$$(1 - L)^{d_o} u_t = v_t, \qquad t = 1, 2, \ldots, \tag{11}$$

TABLE 1. Estimates of d and (95%) confidence bands for the three series. The estimated values of d based on the Whittle function are in bold.

	White noise disturbances		
	No deterministic terms	An intercept	A linear trend
Northern Hemisphere	[0.397 **(0.449)** 0.517]	[0.381 **(0.430)** 0.495]	[0.299 **(0.367)** 0.455]
Southern Hemisphere	[0.416 **(0.480)** 0.569]	[0.405 **(0.466)** 0.556]	[0.338 **(0.418)** 0.529]
Global temperatures	[0.459 **(0.516)** 0.593]	[0.442 **(0.497)** 0.575]	[0.379 **(0.452)** 0.549]
	AR(1) disturbances		
	No deterministic terms	An intercept	A linear trend
Northern Hemisphere	[0.498 **(0.580)** 0.685]	[0.480 **(0.559)** 0.668]	[0.427 **(0.526)** 0.653]
Southern Hemisphere	[0.408 **(0.493)** 0.595]	[0.397 **(0.474)** 0.572]	[0.299 **(0.403)** 0.530]
Global temperatures	[0.497 **(0.582)** 0.688]	[0.481 **(0.560)** 0.664]	[0.413 **(0.516)** 0.641]

and we test H_o (9) for d_o values from 0 to 1 with 0.001 increments using Robinson's (1994) parametric approach. Robinson's (1994) method does not require preliminary differencing; it allows us to test any real value d encompassing stationary and nonstationary hypotheses. Since this method is parametric, we need to specify a functional form for the disturbance term υ_t. First, we suppose υ_t is white noise. Then, an AR(1) structure is considered. In both cases we first suppose that $\alpha = \beta = 0$ [i.e., we do not consider deterministic terms in the undifferenced regression (10)], then an intercept is included (i.e., α unknown and $\beta = 0$ a priori), and finally we include an intercept and a linear time trend (i.e., α and β unknown).

Table 1 shows the test results; the numbers in bold are the maximum likelihood estimates of d obtained with the Whittle function. Table 1 also shows the 95% confidence bands for the nonrejections of d_o using Robinson's (1994) parametric approach. The first noticeable feature observed in this table is that the $I(0)$ hypothesis (i.e., $d = 0$) and the unit root model (i.e., $d = 1$) are both decisively rejected across all cases. Thus, we find strong evidence of fractional integration for the three series. Starting with the case of a white noise model for the disturbance term, we observe that the estimates of d lie between 0.367 and 0.449 for the Northern Hemisphere; they are between 0.418 and 0.480 for the southern temperatures and range between 0.452 and 0.516 for the global temperatures. Thus, the values lie in all cases close to the borderline between stationary and nonstationary processes ($d = 0.5$). Also, if a linear trend is included, the orders of integration are substantially smaller for the three series considered. If we permit $I(0)$ autocorrelation for the error term, the values are generally higher. The estimates are above 0.5 (i.e., in the nonstationary region) for the northern and global temperatures, while they are below 0.5 (and thus stationary) for the Southern Hemisphere.

Table 2 displays for each series and each model the estimates of the coefficients associated with the time trend, along with the estimated value of d and the AR coefficient. We observe that the coefficients for the time trend are all statistically significant. Thus, the warming trend coefficients are 0.60° and 0.54°C for the Northern Hemisphere, respectively, for the cases of white noise and AR(1) disturbances, they are 0.38°C for the two cases in the Southern Hemisphere, and they are 0.47° and 0.44°C for the global temperatures. These

TABLE 2. Estimates of the coefficients associated to the time trend for each series; t values in parentheses. Significant coefficients at the 5% level are in bold.

	White noise disturbances			
	Intercept	Time trend	Estimated d	AR coefficient
Northern Hemisphere	**−0.54327 (−4.860)**	**0.00600 (4.853)**	0.367	—
Southern Hemisphere	**−0.33328 (−3.155)**	**0.00380 (3.106)**	0.418	—
Global temperatures	**−0.42778 (−4.138)**	**0.00470 (3.767)**	0.452	—
	AR(1) disturbances			
	Intercept	Time trend	Estimated d	AR coefficient
Northern Hemisphere	**−0.51509 (−3.200)**	**0.00541 (2.455)**	0.526	−0.276
Southern Hemisphere	**−0.33628 (−3.296)**	**0.00384 (3.301)**	0.403	0.025
Global temperatures	**−0.41471 (−3.529)**	**0.00448 (2.840)**	0.516	−0.111

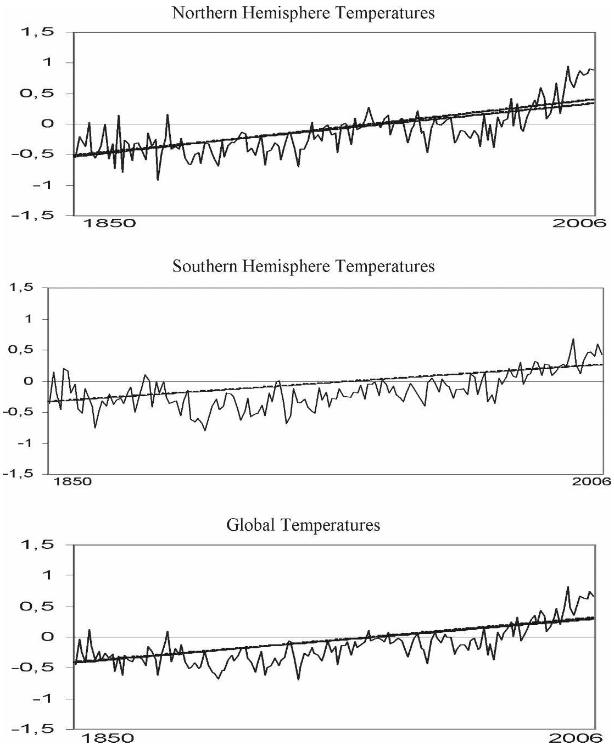

FIG. 2. Original series and linear-fitted trends.

values are smaller than those reported in Jones et al. (2006), where the disturbance term was supposed to be $I(0)$. They are also slightly smaller than those given by Fomby and Vogelsang (2002). These authors proposed a test that is valid under wide distributional assumptions for the error term, including the two standard cases of $I(0)$ and $I(1)$ disturbances. According to these authors, temperatures have increased about 0.5°C (100 yr)$^{-1}$, though they remark that if the analysis is restricted to the twentieth-century data, many of the point trend estimates are closer to 0.6°C.

Figure 2 displays the estimated trends for the three series. It is observed that the strongest trend is in the Northern Hemisphere temperatures, and for the three series the results are fairly similar, independent of the way of modeling the disturbance term.

The results presented so far imply that the time trend has remained fixed across the sample period. This assumption may be unrealistic, especially taking into account that the balance between the greenhouse gases and the sulfur emissions has not remained stable across the years, and this clearly has an effect on the discontinuous changes observed in the temperature time series. Thus, in what follows we consider the possibility of segmented trends and include one structural break at an unknown point in time, using for the estimation the procedure described in section 2. The results for the two cases of white noise and AR(1) disturbances are displayed in Table 3.

Starting with the white noise specification we observe that the break date takes place at 1964 for the Northern Hemisphere, the two time trends are statistically significant, and the orders of integration are 0.348 and 0.479 for the first and second subsamples, respectively. For the southern and global temperatures, the breaks occur in the earlier part of the sample (1891 for the Southern Hemisphere and 1884 for the global temperatures) and the time trends are not significant for the first subsamples. In both series the orders of integration are smaller in the second subsamples.

If we permit an AR(1) process for the disturbance term, the results are displayed in the lower part of Table 3. For the hemispheric temperatures the breaks take place at approximately the same dates as in the white noise case; however, for the global temperatures,

TABLE 3. Estimates based on fractional integration with a structural break; t values in parentheses. Significant coefficients at the 5% level are in bold.

		First subsample				Second subsample			
White noise disturbances									
	Break	Intercept	Linear trend	d	AR	Integration	Linear trend	d	AR cf.
North	1964	**−0.36874 (−3.357)**	**0.00545 (3.316)**	0.348	—	**−2.45729 (−2.719)**	**0.01750 (2.495)**	0.479	—
South	1891	−0.12881 (−0.793)	0.00473 (0.665)	0.437	—	**−0.90066 (−8.290)**	**0.00816 (7.631)**	0.322	—
Global	1884	−0.24101 (−1.583)	0.00107 (1.308)	0.469	—	**−0.80591 (−7.004)**	**0.00750 (6.178)**	0.392	—
AR(1) disturbances									
	Break	Intercept	Linear trend	d	AR	Integration	Linear trend	d	AR cf.
North	1963	**−0.45158 (−5.750)**	**0.00373 (3.353)**	0.257	−0.147	**−3.64315 (−11.63)**	**0.02848 (12.430)**	0.032	−0.011
South	1891	**−0.19745 (−2.253)**	−0.00208 (−0.572)	0.000	0.214	**−0.86801 (−11.36)**	**0.00744 (10.403)**	0.072	0.277
Global	1973	**−0.35264 (−4.445)**	**0.00191 (1.875)**	0.283	0.075	**−3.42123 (−10.44)**	**0.02619 (11.294)**	0.000	−0.087

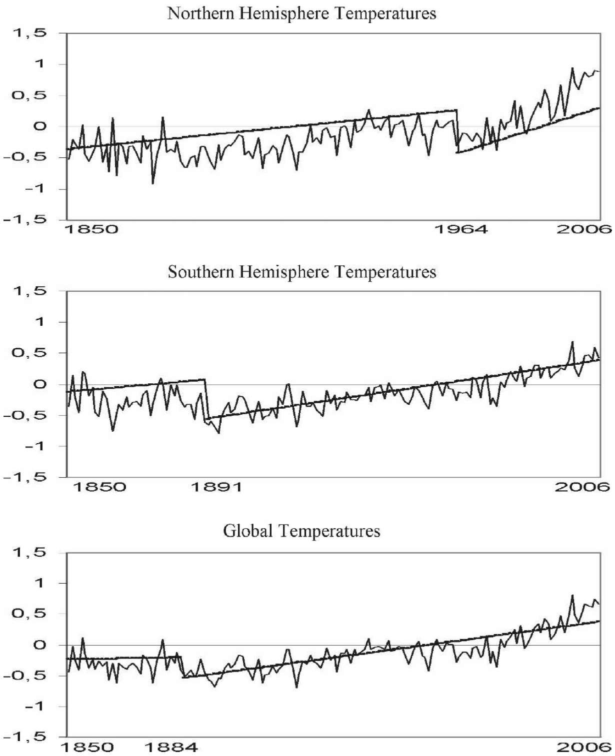

FIG. 3. Original series and segmented trends in case of white noise disturbances.

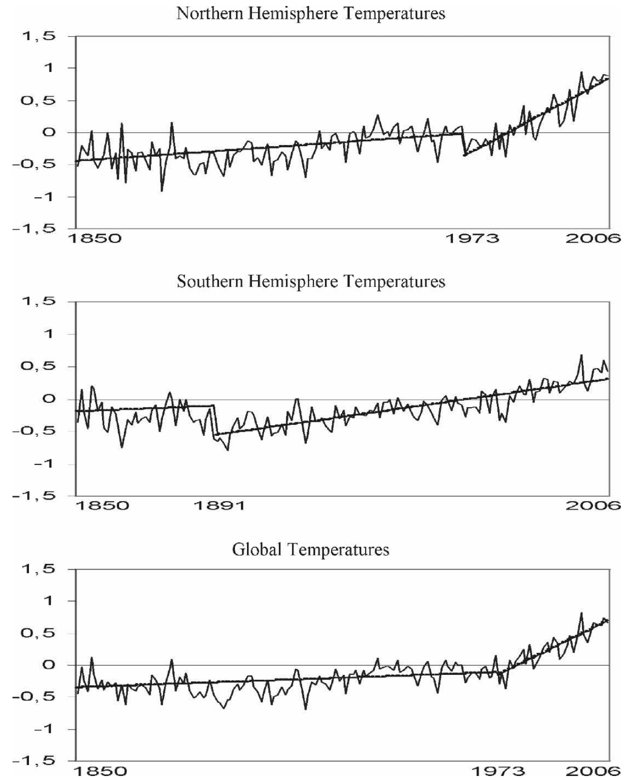

FIG. 4. Original series and segmented trends in case of AR(1) disturbances.

the break occurs now at 1973. The time trend coefficients are significant in practically all cases, the only exception being the southern temperatures during the first subsample, and the estimated values of d are smaller than 0.5 and thus stationary in all cases. In fact, for two cases (southern temperatures in the first subsample, and global temperatures during the second subsample) the estimated value of d is precisely 0, implying a lack of long memory behavior in these two cases.[7]

Figures 3 and 4 reproduce the segmented trends for the three series using white noise and AR(1) errors. Starting with the white noise case (in Fig. 3 and Table 4) we observe that for the northern temperatures, the warming effect changes from 0.54°C before 1964 to 1.75°C after that date; for the southern and global temperatures the warming effect is insignificant during the first subsamples and is about 0.81°C (after 1891) for the southern temperatures and about 0.75°C (after 1884) for the global temperatures.

Assuming that the disturbances follow an AR(1) process (Fig. 4 and Table 4), the change in the warming effect is even more significant: for the northern temperatures, it changes from 0.37° (before 1963) to 2.84°C after the break, it is 0.74°C from 1891 for the Southern Hemisphere, and the values are 0.19° (before 1973) and 2.61°C (after 1973) for the global temperatures.

5. Conclusions

In this article we have examined the existence of significant trends in the global and hemispheric temperature anomaly series, annually, for the time period 1850–2006. However, instead of imposing a priori that the residuals from the estimated trends are stationary $I(0)$, we test this hypothesis by using fractional integration. The results strongly support the view that the northern, southern, and global temperatures are $I(d)$, with d constrained between 0 and 1. Moreover, the existence of a structural break at an unknown point in time is also taken into account, examining the implications that this has on the orders of integration and the coefficients associated with the time trends.

Table 4 summarizes the results in terms of the warming effects, depending on the assumption made on the disturbance term. As expected, the results substantially

[7] Note that the lack of long memory behavior in these two cases may be partly due to the competition between the fractional differencing parameter and the AR coefficient in describing the time dependence.

TABLE 4. Warming effect coefficients according to the different models. Significant coefficients at the 5% level are in bold.

	$d = 0$		Fractional d		Fractional d + segmented trends: First subsample		Fractional d + segmented trends: Second subsample	
	W.N.	AR(1)	W.N.	AR(1)	W.N	AR(1)	W.N.	AR(1)
North	**0.60°C**	**0.69°C**	**0.60°C**	**0.54°C**	**0.54°C**	**0.37°C**	**1.75°C**	**2.84°C**
South	**0.39°C**	**0.70°C**	**0.38°C**	**0.38°C**	0.47°C	-0.20°C	**0.81°C**	**0.74°C**
Global	**0.48°C**	**0.69°C**	**0.47°C**	**0.44°C**	0.10°C	**0.19°C**	**0.75°C**	**2.61°C**

differ from one model to another. Generally, the values are smaller if fractional orders of integration are taken into account. This is consistent with other empirical works that assume $I(0)$ specifications for the error term, also suggesting that the results based on stationary $I(0)$ are upward biased since this hypothesis is strongly rejected when fractional values are taken into account. If segmented trends are permitted, the values are higher during the second subsamples, implying stronger warming effects during the latter parts of the samples.

The results presented in this paper indicate that the temperature anomaly time series are fractionally integrated, implying a strong degree of association between the observations widely separated in time. Nevertheless, the fact that in all cases the fractional differencing parameters are found to be strictly smaller than one also implies that the series are mean reverting. Thus, in the event of an exogenous shock caused, for example, by exogenous forces, there is no strong need of policy actions since the series will return to their original trends sometime in the future. Another implication of these results is that the underlying trends have substantially increased in recent years and the causes of such increases are an issue that will be examined in future papers.

This article can be extended in several other directions. First, the model can be extended to more than a single break, allowing then for the existence of more than two segmented trends in the data. However, for the validity of the type of long memory (fractional integration) model we use in this application it is necessary that the data span a sufficiently long period of time to detect the dependence across time of the observations; given the sample size of the series employed here, the inclusion of two or more breaks would result in relatively short subsamples, therefore invalidating the analysis based on fractional integration. Second, other forms of fractional integration can also be examined. For instance, the detrended series may be $I(d)$ with a pole or singularity in the spectrum occurring at a frequency away from zero. Nonlinear trends can also be considered. Work in these directions is now in progress.

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