The Application of Size Robust Trend Statistics to Global Warming Temperature Series

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ABSTRACT

In this paper we apply some recently proposed size robust trend function tests to seven global temperature series. The tests are valid for general forms of serial correlation in the errors and do not require estimates of serial correlation nuisance parameters in order to carry out asymptotically valid inference. Perhaps more importantly, the tests are valid whether the errors are stationary or have a unit root. This is an important property as conventional trend function tests become oversized when errors have a unit root or are highly persistent. It is this undesirable property of conventional tests that had raised doubts about the empirical validity of a positive trend in global temperature series. Using the robust trend statistics, we find strong evidence to suggest that typical global temperature series spanning back to the mid 1800's have positive trends that are statistically significant. This suggests that average global temperatures are indeed on the rise as widely believed. The point estimates of the rate of increase in the trend suggest that temperatures have risen only about 0.5 degrees Celsius (1.0 degree Fahrenheit) per 100 years.

Key Words: Linear Trend, Serial Correlation, Monte Carlo Simulation, Unit Root.

I. Introduction

In December of 1997, 160 nations having more than 1400 delegates met in Kyoto, Japan at the United Nations Framework Convention on Climate Change (UNFCC) to discuss the "Global Warming Problem." The participation of such a large number of countries and delegates emphasizes the growing international concern about the possibility of global warming. As documented in several publications, if we are going through a sustained period of global warming, the economic consequences of such can be quite substantial. See, for example, Nordhaus (1991).

To date, however, the statistical analyses of global average temperature time series have provided mixed conclusions. For example, Bloomfield and Nychka (1992) found a significant trend in the Hansen and Lebedeff (1987, 88) temperature series at the 0.01 significance level. In contrast, using the same data, Woodward and Gray (1995) provide evidence that the current observed trend in the temperature series may abate in the future as it reverts to the mean. Other contributions to this debate include Bloomfield (1992), Galbraith and Green (1992) and Zheng and Basher (1999) among many others. The purpose of this paper is to revisit the issue of whether or not there is a trend in global average temperature series. We analyze several newly created and extended global average temperature series using a new size robust trend analysis methodology proposed by Vogelsang (1998). The test for significant trend proposed by Vogelsang (1998) is valid in the presence of general forms of serial correlation in the errors of the trend function, with or without a unit root, and can be used without having to estimate the serial correlation parameters either parametrically or nonparametrically. We also apply a trend test analyzed by Bunzel (1998) which is similar is spirit to the tests in Vogelsang (1998).

The average annual temperature series to be analyzed in this paper are plotted in Figures 1 through 7. The figures also plot simple linear trends fitted to each series. The details of the series and their sources are discussed in Appendix B of this paper. Although the series may appear to have upward trends, stationary ARMA models with no trends but with serial correlation of substantial persistence could generate similar data (especially if there is a unit root in the autoregressive representation). See the conclusions of Woodward and Gray (1993) for example. ARMA models fitted to average global temperature series are consistent with positive autocorrelation in the errors that is sometimes highly persistent. Highly persistent errors can lead to the spurious conclusion of a significant trend when using many standard tests because these tests often have inflated size. Thus, when testing for trends in global warming data, it is important to use powerful tests that have size that is robust to highly persistent errors.

The outline of the rest of this paper is as follows. In the next section we review some of the conventional methods previously used in the literature to test for significant trend. In Section III we present size robust trend testing methods proposed by Vogelsang (1998) and Bunzel (1998). These tests are valid whether the errors in the trend model are stationary or have a unit root. We also consider modifications of these tests based on a generalized least squares (GLS) transformation that is valid when the errors in the trend model are stationary. In the following section an empirical analysis of several average global warming series currently being studied by global warming scientists is presented. In Section V we conduct some Monte Carlo experiments to further justify the statistical conclusions of our empirical analysis. Our empirical analysis suggests that many average global temperature series have positive trends that are statistically significant at the 0.01 level. Therefore, there is strong evidence of increasing global temperatures over the past 150 years. It is also important to note that the point estimates of the rate of increase in global temperatures range from 0.39 to 0.54 degrees Celsius per 100 years (about 1.0 degree Fahrenheit per 100 years). We conclude in Section VI of the paper. Proofs are given in Appendix A, and details of the data used in this paper are given in Appendix B.

II. Some Previous Trend Analysis Methods

In testing for a significant trend in time series data, a standard approach has been to assume a trend model of the form

$$y_t = \beta_1 + \beta_2 t + u_t \tag{2.1}$$

where $t = 1, 2, \ldots, T$, y_t represents observations on the time series y at time t, and u_t is the stochastic error in the trend model. The parameter β_2 measures the average change in y_t per time period. Global warming may be occurring if β_2 is positive in which case there is an increasing trend in temperature, y_t. Our null hypothesis is no global warming and our alternative hypothesis is global warming which can written as:

$$\begin{aligned} H_0 &: \beta_2 \le 0 \\ H_1 &: \beta_2 > 0 \end{aligned} \tag{2.2}$$

We are interested in testing a one-sided hypothesis about β_2.

The nature of the error term u_t is crucial in deciding how to proceed in testing (2.2). For example, if the error term u_t follows an AR(1) process

$$u_t = \alpha u_{t-1} + v_t \tag{2.3}$$

where $|\alpha| < 1$ and v_t is i.i.d. $(0, \sigma_v^2)$, the Prais-Winsten (1954) transformation of the model (2.1) is to be recommended. Namely, the time series y_t is transformed as

$$y_1^* = (1 - \hat{\alpha}^2)^{1/2} y_1$$

$$y_t^* = y_t - \hat{\alpha} y_{t-1} \quad , \; t = 2,3,\cdots,T \quad , \tag{2.4}$$

$y^* = (y_1^*, y_2^*, \cdots, y_T^*)'$, while the least squares design matrix

$$\mathrm{X} \;=\; \begin{bmatrix} 1 & 1 \\ 1 & 2 \\ \vdots & \vdots \\ 1 & T \end{bmatrix} \tag{2.5}$$

is transformed to

$$\mathrm{X}^* = \begin{bmatrix} (1-\hat{\alpha}^2)^{1/2} & (1-\hat{\alpha})^{1/2} \\ (1-\hat{\alpha}) & (2-\hat{\alpha}) \\ \vdots & \vdots \\ (1-\hat{\alpha}) & (T-\hat{\alpha}(T-1)) \end{bmatrix} \tag{2.6}$$

and $\hat{\alpha}$ is any consistent estimator of α in equation (2.3). For example, one might choose the least squares estimator of α , namely,

$$\hat{\alpha} = \sum_{t=2}^{T} (\hat{u}_t \hat{u}_{t-1}) \,/\, \sum_{t=2}^{T} \hat{u}_{t-1}^2 \tag{2.7}$$

where $\hat{u}_t$ is the least squares residual at time t obtained by applying least squares to (2.1). Testing the hypothesis (2.2) in this context can proceed by using the test statistic

$$t_{AR(1)} = \beta_2^* \big/ se(\beta_2^*) \tag{2.8}$$

where

$$\beta^* = (\beta_1^*, \beta_2^*)' = (X^{*'} X^*)^{-1} X^{*'} y^* \tag{2.9}$$

is the feasible generalized least squares estimator of $\beta = (\beta_1, \beta_2)'$ in model (2.1) with error specification (2.3) and

$$se(\beta_2^*) = [\tilde{\sigma}_v^2 (X^{*'} X^*)_{22}^{-1}]^{1/2} \tag{2.10}$$

is the standard error of the estimator (2.9). $(X^{*/}X)^{-1}_{22}$ denotes the (2,2) element of the $(X^{*/}X^{*})^{-1}$ matrix. In (2.10) $\widetilde{\sigma}_v^2$ is defined as

$$\widetilde{\sigma}_v^2 = (T-2)^{-1}\sum_{t=1}^{T}\widetilde{v}_v^2 \tag{2.11}$$

which is the sample error variance of v_t and $\widetilde{v}_t$ is the feasible generalized least squares residual obtained as

$$(\widetilde{v}_1, \widetilde{v}_2, \cdots, \widetilde{v}_T)^{/} = y^* - X^*\beta^*. \tag{2.12}$$

Under the assumptions of model (2.1) with (2.3) as the error specification and assuming $H_0\!:\beta_2 = 0$, the statistic $t_{AR(1)}$ 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 arise with $t_{AR(1)}$ when the autocorrelation coefficient α is close to one. It is possible to implement the $t_{AR(1)}$ statistic in a way that controls these size distortions using a conservative approach proposed by Canjels and Watson (1997).

In contrast, if $\alpha = 1$ in (1.3) the appropriate model to pursue is

$$\Delta y_t = y_t - y_{t-1} = \beta_2 + u_t - u_{t-1} = \beta_2 + v_t. \tag{2.13}$$

Then to test $H_0\!:\beta_2 = 0$ one would construct the test statistic

$$t_{fd} = \overline{\beta}_2 \big/ se(\overline{\beta}_2) \tag{2.14}$$

where

$$\overline{\beta}_2 = \overline{\Delta y} = (T-1)^{-1}\sum_{t=2}^{T}\Delta y_t \tag{2.15}$$

is the least squares estimator obtained from (2.13) and $se(\overline{\beta}_2)$ is the corresponding standard error computed as

$$se(\overline{\beta}_2) = \left[(T-2)^{-1} \sum_{t=2}^{T} (\Delta y_t - \overline{\Delta y})^2 \right]^{1/2}. \tag{2.16}$$

Under the assumption of $\alpha = 1$ and $H_0 : \beta_2 = 0$, t_{fd} converges in distribution to a N(0,1) random variable.

Obviously, given the previous discussion, it is quite important to be able to distinguish the stationary (I(0)) case when $|\alpha| < 1$ from the nonstationary (I(1)) case when $\alpha = 1$. In the former case the t-statistic, $t_{AR(1)}$, provides a consistent test (although sometimes suffering finite size-distortion) while t_{fd} provides an inconsistent test. When $\alpha = 1$, t_{fd} provides a consistent test while $t_{AR(1)}$ has size that approaches one as the sample size increases.

Suppose the correlation structure of u_t is more complicated than first order autoregressive and is unknown in which case GLS is not feasible. Suppose that u_t is I(0). From the classic results of Grenander and Rosenblatt (1957) we know that the OLS estimates of β_1 and β_2 are asymptotically equivalent to GLS estimates had the form of serial correlation been known. Therefore, there is no loss in efficiency asymptotically if the OLS estimate of β_2 is used for hypothesis testing. However, to obtain asymptotically valid tests, the asymptotic variance covariance matrix of the OLS estimate of β_2 needs to be consistently estimated. This was the approach taken by Bloomfield and Nychka (1992) for example.

The asymptotic variance of the OLS estimate of β_2 is proportional to the spectral density of u_t at frequency zero. There is a long established literature in time series statistics focusing on the estimation of spectral densities. In recent years, such estimators have been developed in the econometrics literature where there has been focus on testing in models with heteroskedastic serially correlated errors. Using the results of Newey and West (1987, 94) and Andrews (1991) the test of the hypotheses of (2.2) can easily be based on the OLS estimate of β_2. In particular, let $\hat{\beta}_2$ denote the least squares estimator of β_2 in model (2.1), that is, $\hat{\beta} = (\hat{\beta}_1, \hat{\beta}_2) = (X^{\prime}X)^{-1}X^{\prime}y$ where X is defined in (2.5) and y is the $(T \times 1)$ vector of observations on y_t. Consider the heteroscedasticity/autocorrelation consistent (HAC) t-statistic

$$t_{HAC} = \hat{\beta}_2 / se(\hat{\beta}_2) \tag{2.17}$$

where $se(\hat{\beta}_2) = \left[\hat{\sigma}^2 (X^{\prime}X)^{-1}_{22}\right]^{1/2}$, $(X^{\prime}X)^{-1}_{22}$ denotes the (2,2) element of $(X^{\prime}X)^{-1}$,

$\hat{\sigma}^2 = \sum_{j=-(T-1)}^{T-1} K(j / L_T)\hat{\gamma}_j$, $\hat{\gamma}_j = T^{-1}\sum_{t=1}^{T-j}\hat{u}_{t+j}\hat{u}_t$ and $\hat{u}_t = y_t - \hat{\beta}_1 - \hat{\beta}_2 t$. $K(x)$ is a kernel function; e.g. the Bartlett kernel is $K(x) = 1 - |x|$ for $|x| \leq 1$ and $K(x) = 0$ otherwise. L_T denotes the truncation lag or bandwidth. Provided $p\lim \hat{\sigma}^2 = \sigma^2 = \gamma_0^u + 2\sum_{j=1}^{\infty}\gamma_j^u$ where $\gamma_j^u = E(u_t u_{t-j})$ then t_{HAC} converges in distribution to the N(0,1) random variable as long as u_t is stationary (I(0)) and satisfies the necessary mixing and moment conditions. (See Newey and West (1987) and Andrews (1991) for details).

Even though t_{HAC} offers a consistent test of (2.2) in the case of u_t being I(0), the actual size of the test is much larger than the significance level when the errors, u_t, are very persistent. As an illustration, consider the following simulation. Let T = 125 and $u_t = \alpha u_{t-1} + v_t$ where v_t is i.i.d. N(0,1). Furthermore let $H_0{:}\beta_2 = 0$ in model (2.1) and consider testing the one-sided hypothesis given by (2.2) using the 5% one-tail critical values 1.645 taken from the N(0,1) distribution. The empirical rejection probabilities of the t_{HAC} statistic for various values of the autocorrelation coefficient α are

α	Prob

0.8	0.123
0.9	0.162
0.95	0.218
1.0	0.356

These results are based on 1,000 replications using the quadratic spectral kernel to construct $\hat{\sigma}^2$ and employing the automatic truncation lag suggested by Andrews (1991). Obviously, the HAC t-statistic does not work very well in the above situations of high persistence in the errors of the trend function. In addition to obvious size problems for the HAC test, the choices of kernel $K(x)$ and truncation lag L_T add additional dimensions of choice that could cause test results to vary across users.

By way of motivation then, it would be nice if a powerful test were available with size robust to the presence of a unit root or near unit root in u_t and at the same time does not require an estimate of σ^2. Vogelsang (1998) and Bunzel (1998) have proposed such tests. In the next section we focus on those tests and propose a GLS modification to them.

III. Serial Correlation/Unit Root Robust Trend Function Tests

In this section of the paper we will (1) review the trend test statistic labeled $t-PS_T$ recently proposed by Vogelsang (1998) and the trend statistic t^* recently proposed by Bunzel (1998). The statistics are defined shortly. The $t-PS_T$ and t^* statistics are robust to the form of serial correlation in u_t and are valid whether u_t is stationary or u_t has a unit root. In other words, the $t-PS_T$ and t^* statistics, unlike the HAC t-statistic, have correct asymptotic size even if the errors are highly persistent. We also propose simple modifications of the $t-PS_T$ and t^*

statistics based on AR(1) and ARMA(1,1) GLS transformations to prefilter (or pre-whiten) out some of the unknown serial correlation in the errors.

The $t - PS_T$ Statistic

The $t - PS_T$ statistic is a t-statistic based on a partial sums regression that we will introduce below. It offers several advantages over conventional tests of trend (including those of the previous section). First, the test is robust to the possibility of a unit root in the error term. In other words, the test is asymptotically valid whether the errors are stationary or have a unit root. Vogelsang (1998) showed that in finite samples, the test has exact size that is close to the nominal level in sample sizes as small as 100. Second, the test does not require estimates of the serial correlation nuisance parameters and so the choice of estimator for σ^2 or the choice of truncation lag length can be completely avoided.

The $t - PS_T$ test statistic is based on the following partial sum regression

$$z_t = \beta_1 t + \beta_2 [\tfrac{1}{2}(t^2 + t)] + S_t \tag{3.1}$$

where $z_t = \sum_{j=1}^{t} y_j$ and $S_t = \sum_{j=1}^{t} u_j$. Note that z_t and S_t are simply the partial sums of y_t and u_t. Suppose (3.1) is estimated by least squares. Let X_z denote the $(T \times 2)$ matrix of regressors in (3.1). Let t_z denote the standard least squares t-statistic for testing $\beta_2 = 0$. That is,

$$t_z = \widetilde{\beta}_2 \Big/ \left[s_z^2 (X_z' X_z)_{22}^{-1} \right]^{1/2} \tag{3.2}$$

where $\widetilde{\beta}_2$ denotes the least squares estimator of β_2 in model (3.1), $s_z^2 = (T-2)^{-1}\sum_{t=1}^{T}\widetilde{S}_t^2$ is the sample variance of the least squares residuals $\widetilde{S}_t$. The proposed $t-PS_T$ statistic is just $T^{-1/2}$ times expression (3.2)

$$t-PS_T = T^{-1/2}t_z. \tag{3.3}$$

It can be shown that when the errors u_t are stationary, $t-PS_T$ has a well defined asymptotic distribution free of nuisance parameters, and that it yields a consistent test. When the errors u_t have a unit root, $t-PS_T$ still has a well-defined asymptotic distribution, but the distribution is different than when the errors are stationary and its critical values are much larger in magnitude. This fact causes potential size distortions in applications. To illustrate this problem, suppose the errors are stationary, but have an autoregressive root α that is close to one (0.8 is close enough). In finite samples, the exact distribution of $t-PS_T$ will not be well approximated by the distribution valid for stationary errors, and in many cases would be better approximated by the distribution valid for unit root errors. In particular, the stationary critical values will be too small, and exact size will be inflated (perhaps by a large amount).

To get around this size distortion problem, Vogelsang (1998) proposed the following adjustment. Let RSS_y denote the least squares residual sum of squares from regression (2.1). Let RSS_J denote the least squares residual sum of squares from the regression

$$y_t = \beta_1 + \beta_2 t + \sum_{i=2}^{9}\beta_{i+1}t^i + u_t.$$

(3.4)

Define $J_T = (RSS_y - RSS_J) / RSS_J$. Notice that T times J_T is the standard Wald statistic for testing $\beta_3 = \beta_4 = \cdots = \beta_{10} = 0$ in regression (3.4). The J_T statistic is in the class of unit root tests proposed by Park and Choi (1988) and Park (1990) and could be used to test for a unit root in the u_t errors. The J_T statistic is a left-tailed test where a unit root in the errors is rejected for small values of J_T. In particular, Park and Choi (1988) showed that when the errors have a unit root J_T has a well-defined asymptotic distribution while when the errors are stationary $J_T \to 0$.

Let b be a constant. Consider the function $\exp(-bJ_T)$. When the errors have a unit root, $\exp(-bJ_T)$ has a well-defined asymptotic distribution by the continuous mapping theorem. However, when the errors are stationary, $\exp(-bJ_T) \to 1$. Now, suppose we instead define $t-PS_T$ as follows

$$t - PS_T = T^{-1/2} t_z \exp(-bJ_T). \tag{3.5}$$

When the errors are stationary, $t-PS_T$ and $T^{-1/2}t_z$ have the same asymptotic distributions because $\exp(-bJ_T) \to 1$. But, when the errors have a unit root, $t-PS_T$ and $T^{-1/2}t_z$ have different asymptotic distributions. More importantly, notice that for $b > 0$, $\exp(-bJ_T)$ takes on small values because J_T takes on large positive values. Therefore, b can be chosen to shrink the asymptotic distribution of $t-PS_T$ when the errors have a unit root without affecting the asymptotic distribution of $t-PS_T$ when the errors are stationary.

It is not possible to choose b so that the distribution of $t-PS_T$ is the same whether the errors are stationary or have a unit root. But, for a given percentage point (corresponding to a desired significance level), b can be chosen so that the critical values are the same whether the errors are stationary or have a unit root. In Vogelsang (1998) critical values for $t-PS_T$ were tabulated along with the corresponding $b's$. For percentage points 1%, 2.5%, 5%, and 10% the asymptotic critical values (with the $b's$ in the parentheses) are 2.647 (1.501), 2.152 (0.995), 1.720 (0.716) and 1.331 (0.494). These are the critical values appropriate for the one-sided hypothesis we are considering.

The t^* Statistic

We now present a trend test statistic, labeled simply as t^*, taken from Bunzel (1998) and based on the stochastic transformation approach of Kiefer, Vogelsang and Bunzel (2000). The motivation for considering t^* is because it is based on $\hat{\beta}_2$, a more efficient estimator than $\tilde{\beta}_2$. The t^* statistic for testing the null hypothesis (2.2) is calculated as follows. Define $\hat{s}_t = \sum_{j=1}^{t} x_j \hat{u}_j$, where $x_j = (1, j)'$, and let $\hat{C} = T^{-2}\sum_{t=1}^{T}\hat{s}_t\hat{s}_t'$. Define $\hat{B} = (T^{-1}\sum_{t=1}^{T}\hat{x}_t\hat{x}_t')^{-1}\hat{C}(T^{-1}\sum_{t=1}^{T}\hat{x}_t\hat{x}_t')^{-1}$. Let J_T be defined as in the computation of the $t - PS_T$ statistic. Then t^* is defined as

$$t^* = \left(T^{1/2}\hat{\beta}_2 \Big/ \sqrt{\hat{B}_{22}^{-1}}\right)\exp(-bJ_T) \tag{3.6}$$

where $\hat{B}_{22}^{-1}$ denotes the (2,2) element of $\hat{B}^{-1}$, $b = 0.681$ for a 5% one-tailed test, $b = 0.975$ for a 2.5% one-tailed test, and $b = 1.36$ for a 1% one-tailed test. The asymptotic critical values for t^* are 6.46, 8.22, and 10.5, for 5%, 2.5%, and 1% tests, respectively. These critical values are taken from Bunzel (1998). As with the $t - PS_T$ statistic, the t^* statistic is robust to unknown serial correlation and up to one unit root in the errors, and the t^* statistic also does not require an estimate of σ^2.

An ARMA(1,1) Pre-filter

Instead of controlling size distortions because of high serial correlation using the J_T adjustment, we will now consider estimating the trend model (2.1) using an ARMA(1,1) feasible GLS estimator and then computing t_{HAC}, t^*, and $t-PS_T$ statistics on the ARMA(1,1)-transformed data but not using the $\exp(-bJ_T)$ adjustment (that is, implicitly setting $b=0$). We will denote these corresponding test statistics by t^*_{HAC}, t^{**}, and $t-PS^*_T$, respectively.

Using the least squares residuals $\hat{u}_t$ we fit the ARMA(1,1) model

$$\hat{u}_t = \alpha\hat{u}_{t-1} + e_t + \theta e_{t-1} \tag{3.7}$$

and obtain the least squares estimates of α and θ denoted by $\hat{\alpha}$ and $\hat{\theta}$, respectively. We set $e_0 = 0$ so $\hat{\alpha}$ and $\hat{\theta}$ are also conditional MLE estimates if we assume e_t is normally distributed. We obtain the special case of an AR(1) transformation by setting $\hat{\theta}$ = 0. Using results in Tiao and Ali (1971) we can transform the model (2.1) to obtain

$$y^*_t = \beta_1 x^*_{1t} + \beta_2 x^*_{2t} + u^*_t \quad . \tag{3.8}$$

The transformed variables y^*_t, x^*_{1t}, and x^*_{2t} are obtained by applying the following transformation to y_t, 1, and t. Let m_t generically denote y_t, 1, or t. Let $\phi = \hat{\alpha}$ and $\varphi = -\hat{\theta}$. Let $c_1 = m_1$ and define $c_t = \varphi c_{t-1} + m_t - \phi m_{t-1}$, $t = 2,3,\cdots,T$. Let $r_T = c_T$ and define $r_t = \varphi r_{t+1} + c_t$, $t = T-1, T-2, \cdots, 1$. Define $\delta = r_1\left((1-\varphi^{2T})/(1-\varphi^2)\right)\left(1+\sqrt{pq}\right)$ with $p = (1-\phi^2)/(\varphi-\phi)^2$ and $q = p + \left((1-\varphi^{2T})/(1-\varphi^2)\right)$. Then $m^*_t = c_t - \varphi^{t-1}\delta$.

Least squares estimation of (3.8) gives ARMA(1,1) feasible GLS estimates of β_1 and β_2. The t_{HAC} and t^* statistics can be computed as before using least squares and the residuals from

(3.8) resulting in the new statistics t^*_{HAC} and t^{**} , respectively. If we partial sum regression (3.8) we obtain

$$z^*_t = \beta_1 sx^*_{1t} + \beta_2 sx^*_{2t} + s^*_t \tag{3.9}$$

where $z^*_t = \sum_{j=1}^{t} y^*_j$, $sx^*_{1t} = \sum_{j=1}^{t} x^*_{1j}$, $sx^*_{2t} = \sum_{j=1}^{t} x^*_{2j}$ and $s^*_t = \sum_{j=1}^{t} u^*_t$. The $t - PS_T$ statistic is computed as before using least squares estimates of regression (3.9). The idea behind the GLS transformed model is to explicitly account for most of the serial correlation using a parsimonious ARMA(1,1) model, but to still correct for additional serial correlation in the model by using the t^*_{HAC} , t^{**}, and $t - PS^*_T$ statistics. Since the J_T correction is not used, the t^{**} and $t - PS^*_T$ statistics will not be robust to a unit root in u_t . But, they should work well if serial correlation is not too close to a unit root. See the simulations we run below.

It is straightforward to show that t^*_{HAC} , t^{**}, and $t - PS^*_T$ based on the AR(1) transformed model have the same asymptotic null distributions as t_{HAC} , t^* , and $t - PS_T$ provided u_t is stationary. See Appendix A for a proof for $t - PS^*_T$.

IV. Analysis of the Global Warming Data

In this section we analyze seven global annual average temperature series: JWB, JWBENSCO, WH, VGL, JP, MMP, and JOBP. See Appendix B for detailed descriptions of these series and references on each. With the exception of the MMP series, all the series are annual global average temperature series ranging from the mid 1800's to the present. The MMP series is a longer annual series for Central England that goes back to the 1600's. Our statistical analysis using the t_{HAC}, t^*, and $t-PS_T$ statistics is reported in Table 1. For each series (by row) we report (by column) the sample size of each series (T), the least squares estimate of β_2 in the trend model (2.1) ($\hat{\beta}_2$), the OLS estimate of β_2 from the partial sum regression (3.1) ($\tilde{\beta}_2$), the HAC t-statistic (t_{HAC}) using the quadratic spectral kernel and the automatic truncation lag suggested by Andrews (1991), the t^* and $t-PS_T$ statistics (for right-tail 5%, 2.5%, and 1% levels of significance), and the J_T statistic. J_T can be used to test for a unit root in the errors. Recall it is a left tailed test with a unit root in the errors as the null hypothesis. The left-tail 1%, 2.5% and 5% critical values are 0.488, 0.678 and 0.908, respectively. Values of J_T less than these critical values allow rejection of a unit root in the errors. As can be seen from Table 1, it is possible to reject the null of no global warming (reject $H_0 : \beta_2 \leq 0$) for all the series at the 5% level of significance using any of the statistics. Using the t_{HAC} statistic, rejections are possible at the 1% level. However, given that the size of t_{HAC} is not robust to highly persistent errors, those results must be viewed with caution. On the other hand, the null hypothesis can be rejected at the 2.5% level and in a few cases the 1% level using the t^* and $t-PS_T$ statistics. Because these statistics have size that is robust to highly persistent errors, we can be confident these rejections are not spurious artifacts of serial correlation in the errors. Note also that the J_T statistic indicates that the unit root hypothesis can be rejected for the errors of all seven series.

Given that the series appear to have stationary errors, it may be fruitful to apply the ARMA(1,1) (AR(1)) GLS transformed statistics to the series. In Table 2 we report results using the AR(1) transformation and in Table 3 we report results using the ARMA(1,1) transformation. Included in these tables are point estimates of α and θ. The evidence in these two tables is striking. In nearly every case, the null hypothesis can be rejected at the 1% level of significance providing further evidence that the temperature series have a positive statistically significant trend. We show in Monte Carlo simulations in the next section that the GLS transformed statistics have exact size close to the nominal level for values of α and θ that are close to the point estimates of α and θ in the temperature series. Therefore, the results in Tables 2 and 3 can be taken at face value.

We conclude this section with a discussion of the magnitudes of the points estimates of β_2. The points estimates of β_2 range from 0.003295 to 0.005359 depending on the series and method of estimation (we exclude the MMP series from this discussion as that data is not global). These point estimates suggest that global temperatures have increased roughly 0.5 degrees Celsius per 100 years in recent history. The pertinent issue for policy makers is forecasts of future temperature growth. If we take the simple model (2.1) as representative of future behavior of global temperatures (an assumption that may not be true), then we might expect temperatures to increase at roughly the same rate into the future.

V. A Monte Carlo Experiment

In this section we report Monte Carlo simulations that compare the finite sample null rejection probabilities of the previously discussed statistics. The purpose here is to show that t_{HAC} is oversized if u_t has a root close to 1 but that t^* and $t-PS_T$ have size close to the nominal level even if u_t has a unit root. Therefore, a rejection of $H_0:\beta_2=0$ using t^* and $t-PS_T$ is robust to high serial correlation in u_t whereas a rejection using t_{HAC} may be spurious (as pointed out by Woodward and Gray (1993)). The simulations also show that the statistics computed using the ARMA(1,1) transformation have good size unless there is a common factor in the AR and MA components or if α is close 1. If the AR(1) transformation is used, then the common factor problem is avoided and size is good unless α is close 1. The empirical estimates based on the global warming data suggest that the GLS based statistics have reasonable size.

In the simulation we chose the data generating process to be

$$y_t = u_t \tag{5.1}$$

where $u_t = \alpha u_t + e_t + \theta e_{t-1}$, $u_0 = 0$, e_0, and e_t is i.i.d. N(0,1). When we estimate θ, we restrict it to the range (-0.999, 0.999) and we restrict α to the same range. Otherwise, the ARMA(1,1) transformation is not well defined. We only consider size results as we obtain rejections in the data (so power is not an issue, just robustness with respect to size). We report empirical rejection probabilities for the values α = 0.2, 0.3, …, 0.8, 0.9, 0.95, 1.0 and θ = -0.4, 0.0, 0.4. Asymptotic 5% critical values were used.

Figures 8-10 give results for t_{HAC}, t^* and $t-PS_T$. Figures 11-13 give results for the AR(1) transformed statistics. Figures 14-16 give results for the ARMA(1,1) transformed statistics. As can be seen from the figures, t^* and $t-PS_T$ have size close to 0.05 with slight distortions when α = 1 and θ = -0.4. (There is no problem if α = 0.95 and θ = -0.4.) The t_{HAC} statistic is oversized. Even with α = 0.5 and θ = 0.0 the null rejection probability is 0.081 and increases to 0.218 when α = 0.95 and θ = 0.0. The results for t_{HAC} match those reported by Woodward and Gray (1993) so t_{HAC} cannot be trusted in practice. If AR(1) or ARMA(1,1) GLS is used (with no J_T correction) all of the statistics are inflated in size if $\alpha = 1$. But if α < 0.8, the GLS statistics have null rejection probabilities close to 0.05. However, the t^*_{HAC} and t^{**} statistics in the ARMA(1,1) case have problems when the AR and MA roots cancel (α = 0.4 and θ = -0.4) because of a common factor. This occurs because the α and θ parameters are not identified and $\hat{\theta}$ and $\hat{\alpha}$ are often driven to the -1 and 1 borders. The $t - PS^*_T$ statistic does not seem to be affected by this problem. As α approaches 1, t^{**} is less oversized than $t - PS^*_T$ or t^*_{HAC}. Clearly, any results obtained using the GLS based tests must be viewed with caution. However, for several of the series, the point estimates of α and θ reported in Tables 1 – 3 are in the range where size of the GLS transformed tests is reasonably close to the nominal level.

VI. Conclusions

In this paper we applied some recently proposed size robust trend function tests to seven global temperature series. The tests are valid for general forms of serial correlation in the errors and do not require estimates of serial correlation nuisance parameters in order to carry out asymptotically valid inference. Perhaps more importantly, the tests are valid whether the errors are stationary or have a unit root. This is an important property as conventional trend function tests become oversized when errors have a unit root or are highly persistent. It is this undesirable property of conventional tests that had raised doubts about the empirical validity of a statistically significant positive trend in global temperature series.

Using size robust trend statistics, we find strong evidence to suggest that typical global temperature series spanning back to the mid 1800's have positive trends that are statistically significant. This suggests that average global temperatures are indeed on the rise as widely believed. The point estimates of the rate of increase in the trend suggest that temperatures have risen about 0.5 degrees Celsius (1.0 degree Fahrenheit) per 100 years.

Appendix A: Asymptotic Null Distribution of $t-PS_T^*$ Using AR(1) Transformation.

Throughout this appendix, unless otherwise noted, $\sum$ is shorthand notation for $\sum_{t=1}^{T}$.

Assume $T^{-\frac{1}{2}}S_{[rT]} = T^{-\frac{1}{2}}\sum_{t=1}^{[rT]} u_t \Rightarrow \sigma W(r)$ where *[rT]* is the integer part of *rT*. This holds if u_t is *I(0)*. Vogelsang (1998) proved that

$$t-PS_T \Rightarrow \frac{R\left(\int_0^1 G(r)G(r)' \, dr\right)^{-1} \int_0^1 G(r)W(r)dr}{\left[\left(\int_0^1 \widetilde{W}(r)^2 \, dr\right) R\left(\int_0^1 G(r)G(r)' \, dr\right)^{-1} R'\right]^{\frac{1}{2}}}$$

where R=[*0 1*], $G(r) = (r, \frac{1}{2}r^2)'$ and $\widetilde{W}(r) = W(r) - G(r)'\left(\int_0^1 G(r)G(r)' \, dr\right)^{-1} \int_0^1 G(r)W(r)dr$.

Recall $\hat{\alpha}$ as defined by (2.7). When u_t is *I(0),* standard results are $p\lim \hat{\alpha} = \alpha$ and $T^{1/2}(\hat{\alpha} - \alpha) = O_p(1)$. It is convenient to write regression (3.9) in matrix notation as

$$Z^* = SX^*\beta + S^*$$

$$\widetilde{\beta} = \left(SX^{*\prime}SX^*\right)^{-1} SX^{*\prime}Z^* = \beta + \left(SX^{*\prime}SX^*\right)^{-1} SX^{*\prime}S^*.$$

We are interested in the null hypothesis $R\beta = 0$. Under this null we have $R(\widetilde{\beta} - \beta) = R\widetilde{\beta}$.

Therefore we can write

$$t-PS_T^* = \frac{T^{-1/2} R(\widetilde{\beta}-\beta)}{\left[S_{Z*}^2 R\left(SX^{*/} SX^*\right)^{-1} R^/\right]^{1/2}}$$

where $S_{Z*}^2 = T^{-1}\left(Z^{*/}Z^* - Z^{*/}SX^*\left(SX^{*/}SX^*\right)^{-1}SX^{*/}Z^*\right) = T^{-1}\left(S^{*/}S^* - S^{*/}SX^*\left(SX^{*/}SX^*\right)^{-1}SX^{*/}S^*\right)$.

Consider the following limiting results where $\tau_T = \begin{bmatrix} 1 & 0 \\ 0 & T^{-1} \end{bmatrix}$:

$$T^{-3}\tau_T\left(SX^{*/}SX^*\right)\tau_T \Rightarrow (1-\alpha)^2 \int_0^1 G(r)G(r)^/ \, dr. \tag{A1}$$

$$T^{-5/2}\tau_T\left(SX^{*/}S^*\right) \Rightarrow (1-\alpha)^2 \sigma^2 \int_0^1 G(r)W(r)dr. \tag{A2}$$

$$T^{-1}S_{Z*}^2 \Rightarrow (1-\alpha)^2 \sigma^2 \int_0^1 \widetilde{W}(r)^2 \, dr. \tag{A3}$$

(A1) is established as follows. Note that

$$T^{-3}\tau_T\left(SX^{*/}SX^*\right)\tau_T = \begin{bmatrix} T^{-3}\sum SX_{1t}^{*\,2} & T^{-4}\sum SX_{1t}^* SX_{2t}^* \\ T^{-4}\sum SX_{1t}^* SX_{2t}^* & T^{-5}\sum SX_{2t}^{*\,2} \end{bmatrix}.$$

Let $g_1(\hat{\alpha}) = (1-\hat{\alpha}^2)^{1/2} - (1-\hat{\alpha})$ and $g_2(\hat{\alpha}) = (1-\hat{\alpha}^2)^{1/2} - 1$. Simple algebra gives:

$$\begin{aligned}
T^{-3}\sum SX_{1t}^{*\,2} &= T^{-3}\sum\left[t^2(1-\hat{\alpha})^2 + 2t(1-\hat{\alpha})g_1(\hat{\alpha}) + g_1(\hat{\alpha})\right] \\
&= (1-\hat{\alpha})^2 T^{-3}\sum t^2 + o_p(1) \Rightarrow (1-\alpha)^2 \int_0^1 r^2 dr, \\
T^{-4}\sum SX_{1t}^* SX_{2t}^* &= T^{-4}\sum [t(1-\hat{\alpha}) + g_1(\hat{\alpha})][(1-\hat{\alpha})\frac{1}{2}(t^2+t) + \hat{\alpha}t + g_2(\hat{\alpha})] \\
&= (1-\hat{\alpha})^2 T^{-4}\sum \frac{1}{2}t^3 + o_p(1) \Rightarrow (1-\alpha)^2 \int_0^1 \frac{1}{2} r^3 dr, \\
T^{-5}\sum SX_{2t}^{*\,2} &= T^{-5}\sum\left[(1-\hat{\alpha})\frac{1}{2}\left(t^2+t\right) + \hat{\alpha}t + g_2(\hat{\alpha})\right]^2 = (1-\alpha)^2 T^{-5}\sum \frac{1}{4}t^4 + o_p(1) \\
&\Rightarrow (1-\alpha)^2 \int_0^1 \frac{1}{4} r^4 dr.
\end{aligned}$$

(A1) directly follows using the fact that

$$\int_0^1 G(r)G(r)' dr = \begin{bmatrix} \int_0^1 r^2 dr & \int_0^1 \frac{1}{2} r^3 dr \\ \int_0^1 \frac{1}{2} r^3 dr & \int_0^1 \frac{1}{4} r^4 dr \end{bmatrix}.$$

(A2) is established as follows. Note that $T^{-5/2}\tau_T\left(SX^{*\prime}SX^*\right) = \begin{bmatrix} T^{-5/2}\sum SX_{1t}^* S_t^* \\ T^{-7/2}\sum SX_{2t}^* S_t^* \end{bmatrix}$.

Using $S_t^* = \sum_{j=2}^{t}\left(u_j - \hat{\alpha}u_{j-1}\right) + (1-\hat{\alpha}^2)^{1/2}u_1 = \sum_{j=2}^{t}\left(u_j - \alpha u_{j-1}\right) - (\hat{\alpha}-\alpha)\sum_{j=2}^{t} u_{j-1} + (1-\hat{\alpha}^2)^{1/2}u_1$, we have

$$\begin{aligned} T^{-1/2}S_{[rT]}^* &= T^{-1/2}\sum_{t=2}^{[rT]}(u_t - \alpha u_{t-1}) - T^{1/2}(\hat{\alpha}-\alpha)T^{-1}\sum_{t=2}^{[rT]}u_{t-1} + T^{-1/2}(1-\hat{\alpha})^{1/2}u_1 \\ &= T^{-1/2}\sum_{t=2}^{[rT]}(u_t - \alpha u_{t-1}) + o_p(1) \Rightarrow (1-\alpha)\sigma W(r). \end{aligned} \tag{A4}$$

Simple algebra along with (A4) gives

$$\begin{aligned} T^{-5/2}\sum SX_{1t}^* S_t^* &= T^{-5/2}\sum\left(t(1-\hat{\alpha}) + g_1(\hat{\alpha})\right)S_t^* = (1-\hat{\alpha})T^{-5/2}\sum tS_t^* \\ &\Rightarrow (1-\alpha)^2\sigma\int_0^1 rW(r)dr, \\ T^{-7/2}\sum SX_{2t}^* S_t^* &= T^{-7/2}\sum\left[(1-\hat{\alpha})\frac{1}{2}\left(t^2+t\right) + \hat{\alpha}t + g_2(\hat{\alpha})\right]S_t^* \\ &= (1-\hat{\alpha})T^{-7/2}\sum\frac{1}{2}t^2 S_t^* + o_p(1) \Rightarrow (1-\alpha)^2\sigma\int_0^1\frac{1}{2}r^2 W(r)dr. \end{aligned}$$

(A2) follows directly using the fact that

$$\int_0^1 G(r)W(r)dr = \begin{bmatrix} \int_0^1 rW(r)dr \\ \int_0^1 \frac{1}{2}r^2 W(r)dr \end{bmatrix}.$$

Using simple algebra, (A1), (A2), and the fact that $T^{-2}\sum S_t^{*2} \Rightarrow (1-\alpha)^2\sigma^2\int_0^1 W(r)^2 dr$, (A3) is established by

$$T^{-1}S_{Z*}^{2} = T^{-2}S^{*/}S^{*} - T^{-5/2}S^{*/}SX^{*}\tau_T\left(T^{-3}\tau_T SX^{*/}SX^{*}\tau_T\right)^{-1}\tau_T SX^{*/}S^{*}T^{-5/2}$$

$$\Rightarrow (1-\alpha)^2\sigma^2\left[\int_0^1 W(r)^2\,dr - \int_0^1 G(r)^{/}W(r)dr\left(\int_0^1 G(r)G(r)^{/}\,dr\right)^{-1}\int_0^1 G(r)W(r)dr\right]$$

$$= (1-\alpha)^2\sigma^2\int_0^1 \widetilde{W}(r)^2\,dr. \qquad \text{(A5)}$$

Using (A1) and (A2) we have

$$T^{1/2}\tau_T^{-1}(\widetilde{\beta}-\beta) = T^{1/2}\tau_T^{-1}\left(SX^{*/}SX^{*}\right)^{-1}SX^{*/}S^{*}$$

$$= \left(T^{-3}\tau_T SX^{*/}SX^{*}\tau_T\right)^{-1}T^{-5/2}\tau_T SX^{*/}S^{*}$$

$$\Rightarrow \sigma^2\left(\int_0^1 G(r)G(r)^{/}\,dr\right)^{-1}\int_0^1 G(r)W(r)dr.$$

We now have all the components needed to complete the proof. Using simple algebra we have

$$t-PS_T^{*} = \frac{TR\tau_T T^{1/2}\tau_T^{-1}\left(\widetilde{\beta}-\beta\right)}{\left[T^{-1}S_{Z*}^{2}TR\tau_T\left(T^{-3}\tau_T SX^{*/}SX^{*}\tau_T\right)^{-1}\tau_T R^{/}T\right]^{1/2}}.$$

Using the fact that $TR\tau_T = R$ and applying (A1), (A3) and (A5) we obtain

$$t-PS_T^{*} = \frac{RT^{1/2}\tau_T^{-1}\left(\widetilde{\beta}-\beta\right)}{\left[T^{-1}S_{Z*}^{2}R\left(T^{-3}\tau_T SX^{*/}SX^{*}\tau_T\right)^{-1}R^{/}\right]^{1/2}} \Rightarrow \frac{R\left(\int_0^1 G(r)G(r)^{/}\,dr\right)^{-1}\int_0^1 G(r)W(r)dr}{\left[\left(\int_0^1 \widetilde{W}(r)^2\,dr\right)R\left(\int_0^1 G(r)G(r)^{/}\,dr\right)^{-1}R^{/}\right]^{\frac{1}{2}}}$$

which completes the proof.

Similar calculations can be used to show that t^{*} and t^{**} have the same asymptotic null distribution.

Appendix B: Data Appendix for Global Warming Data

JWB and JWBENSCO

P.D. Jones, T.M.L. Wigley, K.R. Briffa

Citation: Jones, P.D., T.M.L. Wigley, and K.R. Briffa, 1994. Global and hemispheric temperature anomalies--land and marine instrumental records.pp.603-608. In T.A. Boden, D.P. Kaiser, R.J. Sepanski, and F.W. Stoss (eds.), Trends '93: A Compendium of Data on Global Change. ORNL/CDIAC-65. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, Tenn., U.S.A.

Period of Record: 1854-1993 (relative to a 1950-79 reference period)

Methods:

These global and hemispheric temperature anomaly estimates were compiled by Jones et al. (1986a,b,c), Jones (1988a,b), Jones and Wigley (1990), and Jones et al. (1991) and are based on corrected land and marine data. Land data were derived from meteorological data and fixed-position weather ship data that were corrected for non climatic errors, such as station shifts and/or instrument changes (Jones et al. 1985, 1986d; Jones and Wigley 1990; Jones and Briffa 1992). The marine data were from the Comprehensive Ocean-Atmosphere Data Set (COADS) compilation (Woodruff et al. 1987) and sea surface temperature (SST) estimates produced by the United Meteorological Office (Bottomley et al. 1990). Both SSTs and marine air temperatures were corrected, but only SST data were used in the combined land-marine data set. Two series of global and hemispheric temperature anomaly estimates are provided, one adjusted for the influence of El Nino/Southern Oscillation (ENSO) events and the other uncorrected for ENSO events. The ENSO influence was extracted by using regression techniques (Jones 1988b, Angell 1990).

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Briffa, K.R. and P.D. Jones 1993. Global surface air temperature variations during the twentieth century: Part 2, implications for large-scale high-frequency palaeoclimatic studies. The Holocene 3:77-88.

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WH

H. Wilson and J. Hansen

Citation: Wilson, H. and J. Hansen. 1994. Global and hemispheric temperature anomalies from instrumental surface air temperature records. Pp. 609-614. In T.A. Boden, D.P. Kaiser, R.J. Sepanski, and F.W. Stoss (eds.), Trends '93: A Compendium of Data on Global Change. ORNL/CDIAC-65. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, Tenn., U.S.A.

Period of Record: 1880-1993 (relative to a 1951-80 reference period)

Methods:

Temperature change over the past century is calculated from surface air temperatures published in the World Weather Records and the World Meteorological Organization's Monthly Climatic Data for the World, supplemented by monthly mean station records available from NOAA's Climate Analysis Center a few days after the end of each month. At a given gridpoint, data from all nearby stations are combined to form an estimate of the temperature change, essentially as described by Hansen and Lebedeff (1987). The gridded data are combined to ultimately obtain estimates for the temperature change record of regions, latitudinal zones, the hemispheres, and the globe.

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VGL

K. Ya. Vinnidov, P. Ya. Groisman, K.M. Lugina

Citations: Vinnikov, K. Ya., P. Ya. Groisman, and K.M. Lugina. 1994. Global and hemispheric temperature anomalies from instrumental surface air temperature records. Pp. 615-627. In T.A. Boden, D.P. Kaiser, R.J. Sepanski, and FW. Stoss (eds.), Trends '93: A Compendium of Data on Global Change. ORNL/CDIAC-65. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, Tenn., U.S.A.

Period of Record: 1881-1993 (relative to a 1951-75 reference period)

Methods:

The mean monthly and annual values of surface air temperature compiled by Vinnikov et al. have been taken mainly from the World Weather Records, Monthly Climatic Cata for the World, and Meteorological Data for Individual Years over the Northern Hemisphere Excluding the USSR. These published records were supplemented with information from different national publications. After removal of station records believed to be inhomogeneous or biased, 301 and 265 stations were used to determine the mean temperatures for the Northern and Southern hemispheres, respectively. The departures of the individual station mean monthly temperatures from an average for the period from 1951 to 1975 were spatially averaged. Details on the spatial averaging method may be found in Kagan(1979), Vinnikov and Lugina (1982), Groisman and Lugina (1985), and Vinnikov et. Al. (1987, 1990).

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JP

P.D. Jones and D.E. Parker, et al.

Citations:

P.D. Jones, Journal of Climate, 7, 1794-1802 (1994).

D.E. Parker et al., Climatic Change, 31, 559-600 (1995).

Source: The Met.Office, Hadley Centre, London, England: http://www.meto.govt.uk/

COMBINED LAND AIR AND SEA SURFACE TEMPERATURE ANOMALIES FOR THE GLOBE

Values are temperature difference, in degrees C, from the 1961 average.

Period of Record: Global Annual Values 1851-1997.

MMP

G. Manley (1953), G. Manley (1974), and D.E. Parker, et al. (1992)

MONTHLY CENTRAL ENGLAND TEMPERATURE

Citations:

Manley, G. 1953. The mean temperature of Central England, 1698 to 1952. Q.J.R. Meteorol. Soc., Vol 79, p242-261.

Manley, G. 1974. Central England Temperatures: monthly means 1659 to 1973. Q.J.R. Meteorol. Soc., Vol 100, p389-405.

Parker, D.E., T.P. Legg, And C.K. Folland. 1992. A new daily Central England Temperature Series, 1772-1991. Int. J. Clim., Vol 12, p317-342.

Period of Record: 1659- May, 1998 monthly.

Methods:

These temperatures are representative of a roughly triangular area of the United Kingdom enclosed by Preston, London and Bristol. The monthly series, which begins in 1659, is the longest available instrumental record of temperature in the world.

Manley (1953, 1974) compiled most of the monthly series, covering 1659 to 1973. These data were updated to 1991 by Parker et al. (1992) and are now kept up to date by the Climate Data Monitoring section of the Hadley Centre, Met Office. Since 1974 the data have been adjusted to allow for urban warming.

JOBP

This data set was recently posted on the website of the Carbon Dioxide Information Analysis Center, Oak Ridge Laboratory, Oak Ridge, Tennessee, U.S.A. That website is http://cdiac.esd.ornl.gov/ftp/trends/temp/jonesscru/global.dat.

Global Monthly and Annual Temperature Anomalies (degrees C), 1856-1997

(Relative to the 1961 - 1990 Mean)

(February, 1998)

Source: P.D. Jones
T.J. Osborn
K.R. Briffa
Climatic research Unit
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University of East Anglia
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Hadley Centre for Climate Prediction and Research
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United Kingdom

This data set (in terms of the global average annual temperatures) is duplicated in a data set labeled tavegl.dat that I obtained from the Climatic Research Unit, School of Environmental Sciences, University of East Anglia, Norwich NR4 7TJ, UK. However, the JOBP data set does have the 1998 data, which is posted in tavegl.dat. Evidently, this data set is maintained by P.D. Jones. The website for the tavegl.dat data set is http://www.cru.uea.ac.uk/cru/data/temperat.htm.

The format for this data set is:

for years = 1856 to 1998; format (i5,13f7.2) year, 12 monthly values, annual value;
format (i5, 12i7) year, 12 percentage coverage values of the globe.

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***For references on the global warming data series analyzed in this paper see Appendix B.**

TABLE 1

Empirical Results for

Temperature Series:

Standard Regressions

				t^*				$t-PS_T$			
Series	T	$\hat{\beta}_2$	t_{HAC}	5%	2.5%	1%	$\tilde{\beta}_2$	5%	2.5%	1%	J
JWB	140	0.004155	10.75^a	10.24^c	9.069^b	7.736	0.003732	3.490^c	3.111^b	2.524	0.4128***
JWBE	125	0.004429	10.05^a	10.60^c	9.029^b	7.316	0.004114	3.488^c	2.994^b	2.271	0.5465**
WH	114	0.005359	10.11^a	18.15^c	15.75^b	13.08^a	0.005277	3.550^c	3.104^b	2.432	0.4819***
VGL	113	0.005184	8.937^a	16.24^c	14.07^b	11.66^a	0.005065	3.160^c	2.757^b	2.154	0.4883***
JP	147	0.003875	8.375^a	6.292^c	4.969	3.647	0.003295	2.001^c	1.599	1.065	0.8033*
MMP	339	0.002111	5.082^a	10.54^c	10.20^b	9.764	0.001675	2.438^c	2.362^b	2.231	0.1128***
JOBP	143	0.004292	8.614^a	6.408	4.959	3.545	0.003699	2.103^c	1.649	1.060	0.8720*

Critical Values for Test Statistics

%	t_{HAC}	t^*	$t-PS_T$
0.950	1.645	6.46	1.720
0.975	1.960	8.22	2.152
0.990	2.330	10.5	2.647

Notes: The superscripts a, b, can c denote rejection of the null hypothesis of no global warming at the 1%, 2.5%, and 5% levels of significance, respectively. The superscripts ***, **, and * denote rejection of a unit root in the errors at the 1%, 2.5%, and 5% levels of significance, respectively.

TABLE 2

Empirical Results for Temperature Series:

AR(1) Transformation Used

Series	T	$\hat{\alpha}$	$\hat{\beta}_2$	t^*_{HAC}	t^{**}	$\tilde{\beta}_2$	$t-PS^*_T$
JWB	140	0.4466	0.004095	9.576[a]	12.57[a]	0.004137	5.998[a]
JWBE	125	0.5941	0.004424	8.462[a]	13.59[a]	0.004499	6.225[a]
WH	114	0.4259	0.005334	9.303[a]	26.00[a]	0.005334	4.529[a]
VGL	113	0.4603	0.005192	8.092[a]	23.42[a]	0.005070	4.067[a]
JP	147	0.5740	0.003884	7.953[a]	9.556[b]	0.003725	4.219[a]
MMP	339	0.2085	0.002125	5.348[a]	11.27[a]	0.001670	2.582[b]
JOBP	143	0.6260	0.004444	7.739[a]	10.40[b]	0.003914	3.915[a]

Critical Values for Test Statistics

%	t^*_{HAC}	t^{**}	$t-PS^*_T$
0.950	1.645	6.46	1.720
0.975	1.960	8.22	2.152
0.990	2.330	10.5	2.647

Notes: The superscripts *a, b,* and *c* denote rejection of the null hypothesis of no global warming at the 1%, 2.5% and 5% levels of significance, respectively.

TABLE 3

Empirical Results for Temperature Series:

ARMA(1,1) Transformation Used

Series	T	$\hat{\alpha}$	$\hat{\theta}$	$\hat{\beta}_2$	t^*_{HAC}	t^{**}	$\tilde{\beta}_2$	$t - PS^*_T$
JWB	140	0.4628	-0.02028	0.004094	9.456[a]	12.56[a]	0.004146	6.013[a]
JWBE	125	0.5217	0.11080	0.004418	9.071[a]	13.89[a]	0.004433	6.095[a]
WH	114	0.4621	-0.04428	0.005331	9.131[a]	26.05[a]	0.005338	4.481[a]
VGL	113	0.3486	0.14120	0.005199	8.539[a]	23.31[a]	0.005063	4.178[a]
JP	147	0.8278	-0.40950	0.003907	5.475[a]	8.512[b]	0.004271	4.069[a]
MMP	339	0.7586	-0.57510	0.002139	3.954[a]	10.66[a]	0.001813	2.428[b]
JOBP	143	0.6934	-0.10860	0.004481	7.195[a]	10.23[a]	0.003949	3.828[a]

Critical Values for Test Statistics

%	t^*_{HAC}	t^{**}	$t - PS^*_T$
0.990	1.645	6.46	1.720
0.975	1.960	8.22	2.152
0.990	2.330	10.5	2.647

Notes: The superscripts *a, b,* and *c* denote rejection of the null hypothesis of no global warming at the 1%, 2.5% and 5% levels of significance, respectively.

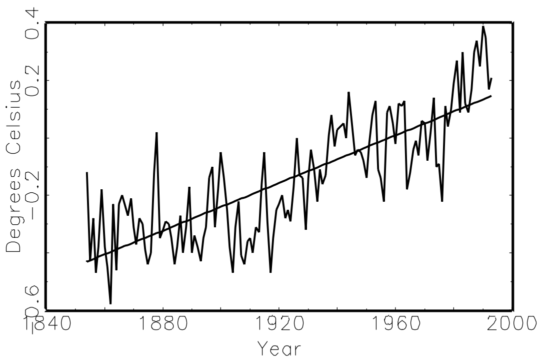

Figure 1: JWB Series

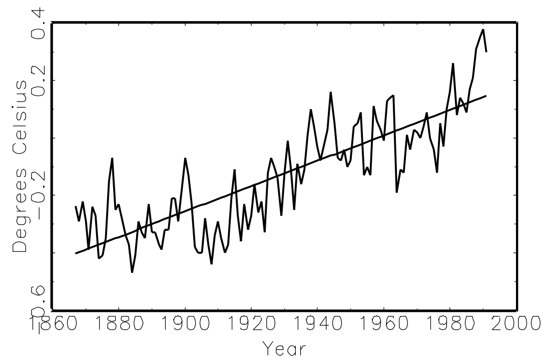

Figure 2: JWBENSCO Series

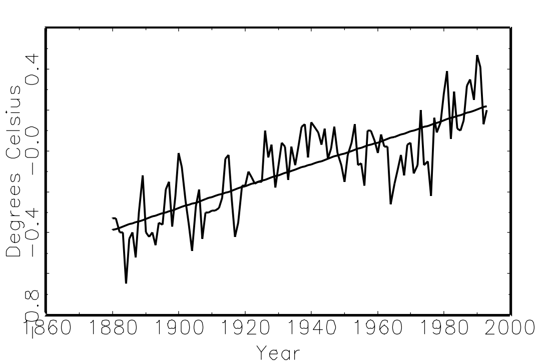

Figure 3: WH Series

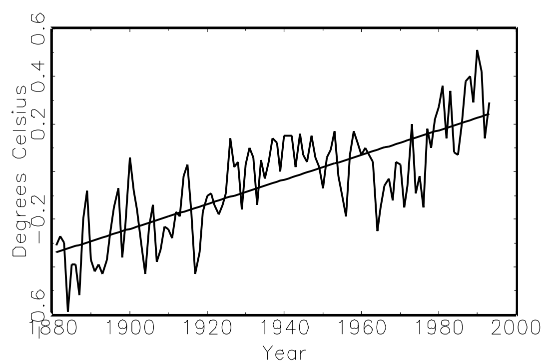

Figure 4: VGL Series

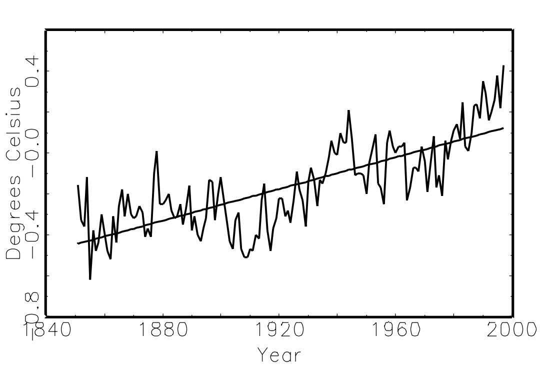

Figure 5: JP Series

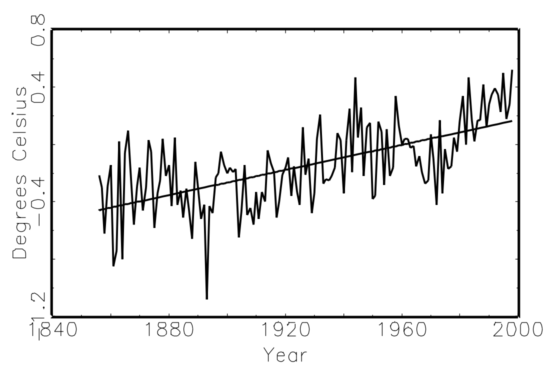

Figure 6: JOBP Series

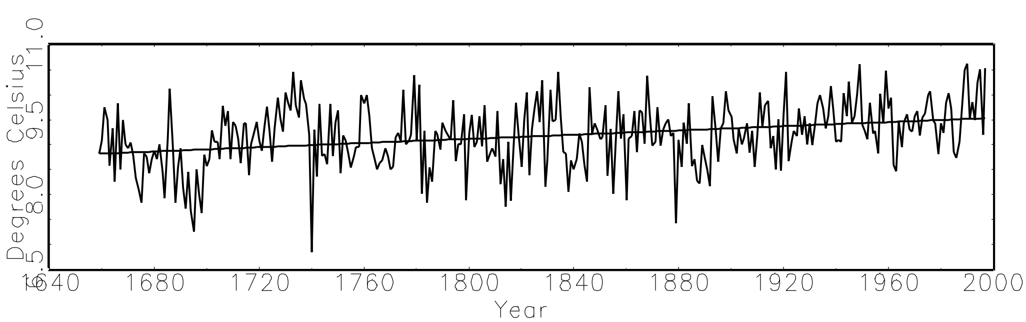

Figure 7: MMP Series

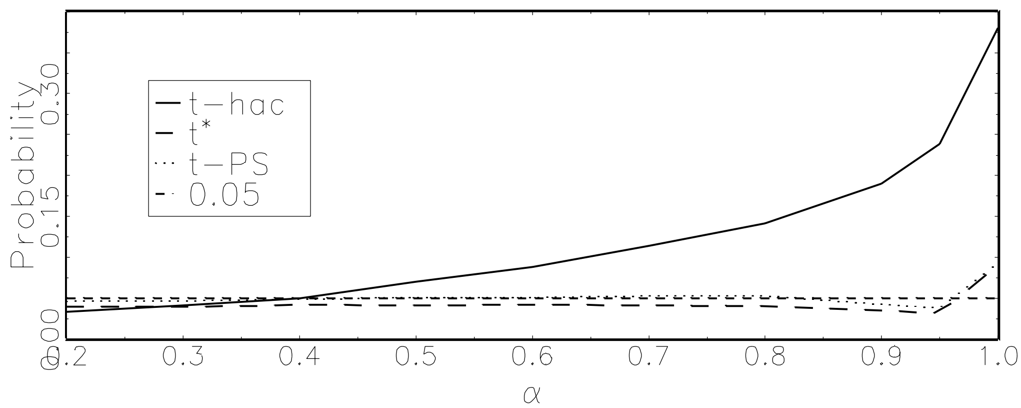

Figure 8: Null Rejection Probabilities Θ=−0.4

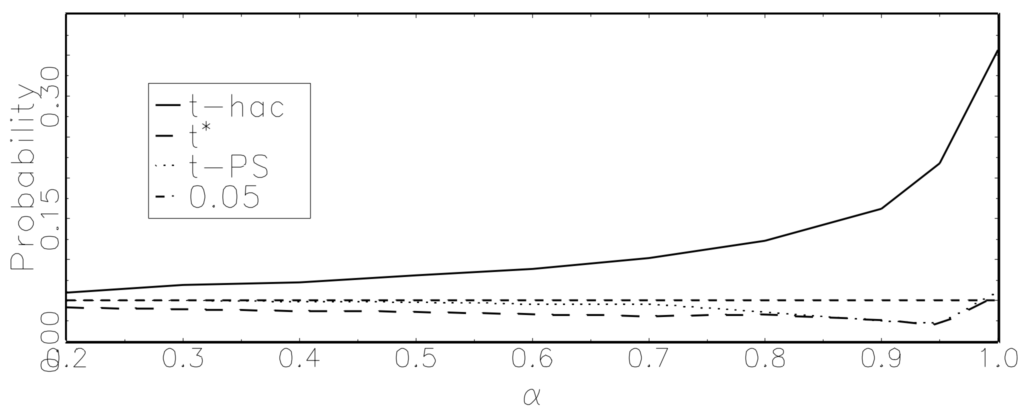

Figure 9: Null Rejection Probabilities Θ=0.0

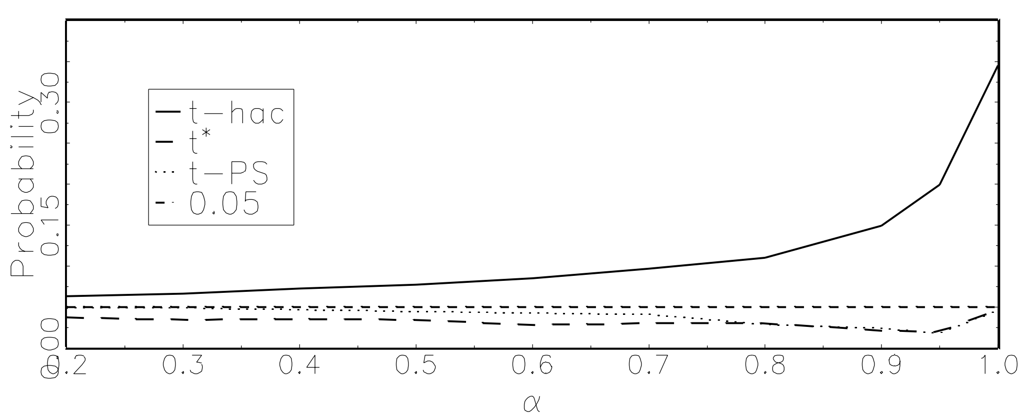

Figure 10: Null Rejection Probabilities Θ=0.4

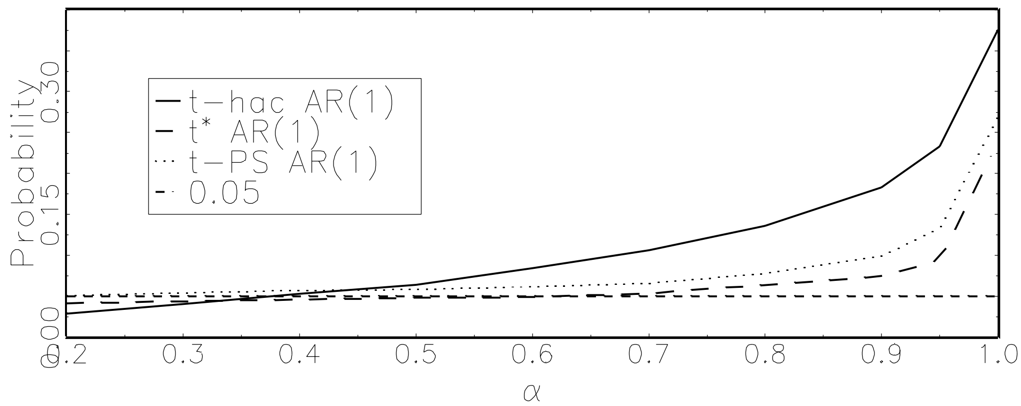

Figure 11: Null Rejection Probabilities Θ=−0.4

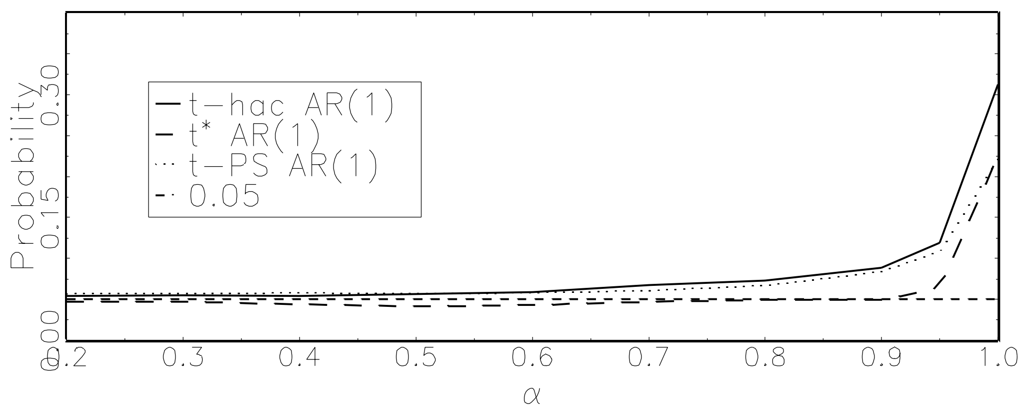

Figure 12: Null Rejection Probabilities Θ=0.0

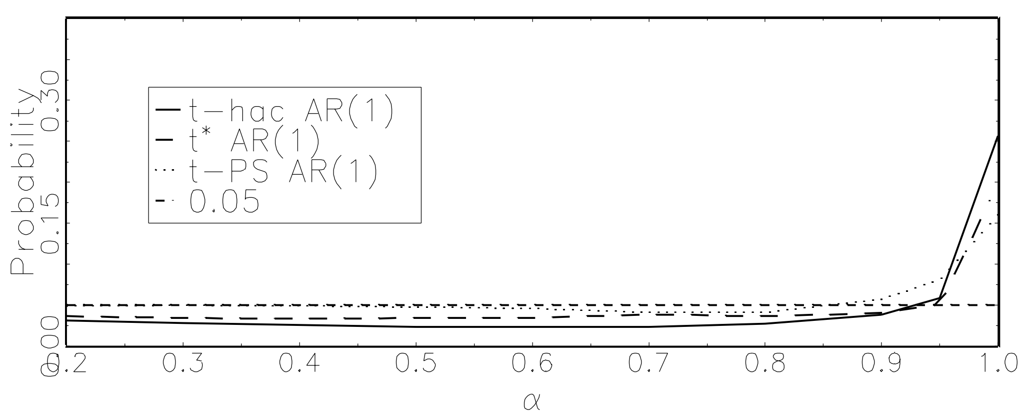

Figure 13: Null Rejection Probabilities Θ=0.4

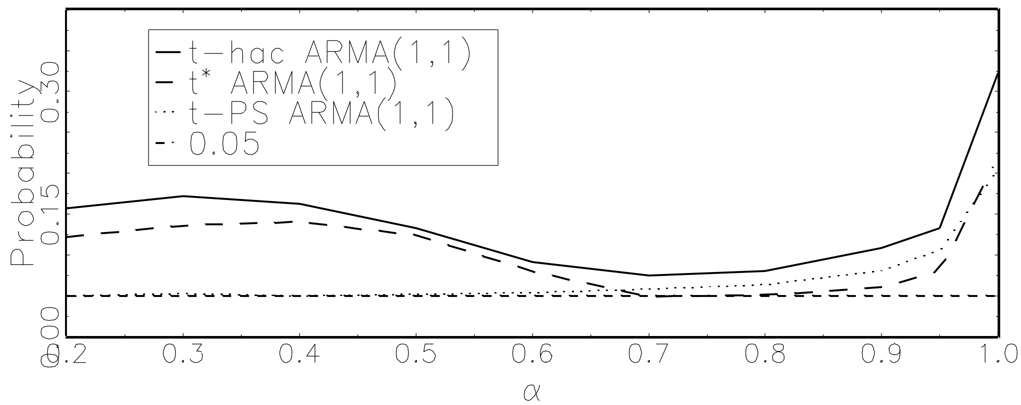

Figure 14: Null Rejection Probabilities Θ=−0.4

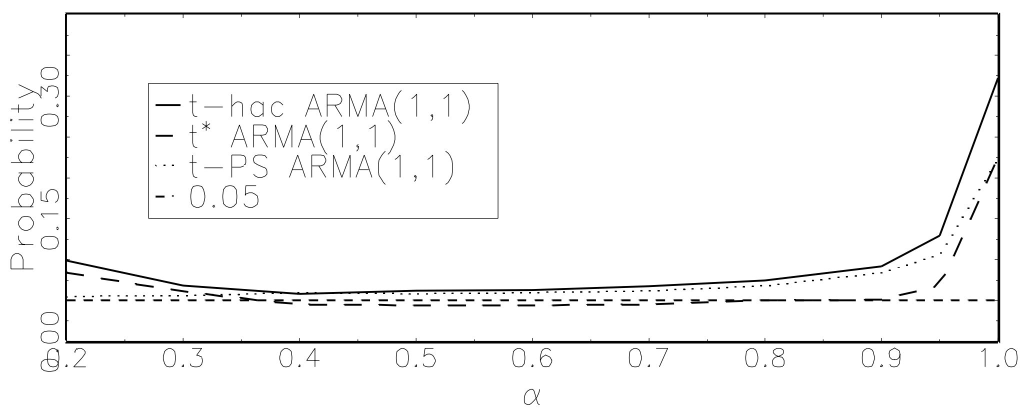

Figure 15: Null Rejection Probabilities Θ=0.0

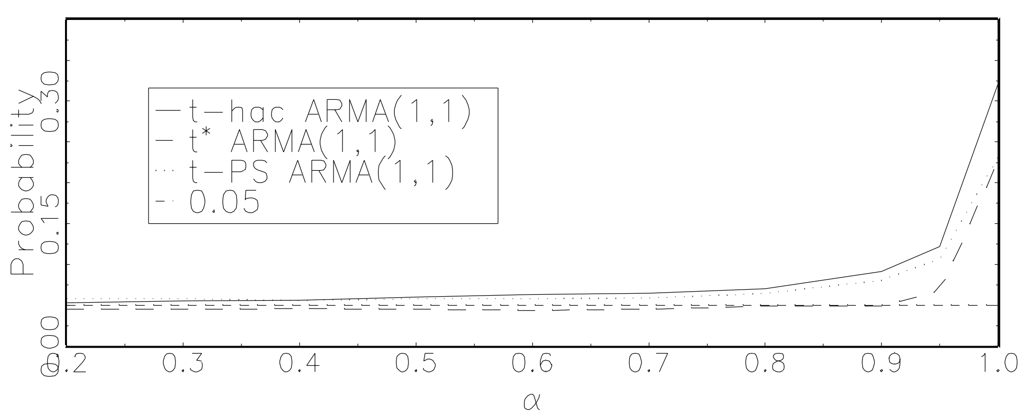

Figure 16: Null Rejection Probabilities Θ=0.4