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Global Warming Trend:

Further Evidence from Multivariate Long Memory Models of Temperature and Tree Ring Series*

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<Content>

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I. Introduction

There are two reasons for econometricians to be interested in temperature and tree ring time series data. First, and most obviously, the issue of global warming and adverse climatic change is clearly of great interest to scientists and mankind. Any additional insights that time series econometricians can throw on the situation will be of value. Many studies, e.g. Frisvold and Kuhn (1998) make the assumption that human economic activity has already had detectable effects on world climate, and seem to regard this as a proven fact. Before implementing costly economic policies to halt climatic change, policy makers and the scientific community have to assemble sufficient statistical evidence to make an informed decision.

The second reason for econometricians to become involved with this issue, concerns the growth of interest in recent years with the topic of long memory and fractional integration in economic time series data. While the presence of long memory in the volatility process of asset prices seems close to an undisputed fact, e.g. Ding, Granger and Engle (1993), Baillie, Bollerslev and Mikkelsen (1996); the relevance and validity of the theory for the conditional mean of economic variables is extremely unclear. In particular, this point has been convincingly argued by Granger (1981) that the possibility of multiple break points causes the appearance of a "spurious" form of long memory. Also, many studies have failed to find convincing evidence for the phenomenon in macroeconomic time series; see Sowell (1992), etc.

With these issues in mind, the present paper examines the occurrence of long memory in data that has significance for the important arena of global warming. These series are also the type of physical data originally analyzed by Hurst (1951) when he developed the theory of long memory processes. It is of interest to see if modern time series methods can confirm Hurst's original intuition that he based on simple R/S analysis of other geophysical time series.

Before considering the econometric details of our study, it is first worth considering the background to the global warming debate. In particular, there appear to be several difficulties with the implicit assumption that human economic activity has necessarily lead to global warming:

(i) Recorded temperature series, which exist for the last 150 years, indicate that the greatest increase in the world's temperature appeared to have occurred in the first 75 years, while the greatest increase in greenhouse gas emissions occurred in the last 75 years. This seems counter to the global warming theory.

(ii) Also, satellite data of the upper atmosphere does not show evidence of warming.

(iii) Recently there is evidence that solar activity is related to temperature. Clearly, this variable is genuinely exogenous to human economic activity.

The contribution of this paper is to develop a trend stationary, multivariate long memory model to represent the time series behavior of annual temperature, and to simultaneously estimate models for the various temperature series recorded at different locations. The model is also applied to series of tree rings, which are often used as proxies for temperature. The model is surprisingly simple and provides a very good description of the dynamics of temperature readings from different parts of the world. The model also allows for a test that temperature and tree rings are increasing over time.

This paper is strongly motivated by the interesting recent article of Seater (1993), which appears to be one of the relatively few rigorous statistical time series studies of temperature data. This seems very surprising given the importance of the issue. Seater (1993) estimated quite high order ARMA(p, q) models around a linear time trend and concluded that the data was consistent with an increase of 0.45 Celsius degrees per hundred years.[1] Although the 95% confidence intervals of 0.15 to 0.75 were relatively wide, they nevertheless imply an unambiguous support for the hypothesis of global warming based on the analysis of measured temperature data since 1850.

Section 5 of this paper examines long series of the width of tree rings, which are frequently used to reconstruct past climatic conditions. Again, relatively simple, fractional white noise models are found to be remarkably successful in representing the conditional mean of the temperature and tree ring data. These models are consistent with the Hurst effect which has been discovered for other geophysical data. Accordingly, estimates are reported for both univariate and multivariate fractional models.

We find both the long memory parameter and the time trend parameter

1) Although the 95% confidence intervals of 0.15 to 0.75 were relatively wide, they nevertheless imply an unambiguous support for the hypothesis of global warming based on the analysis of measured temperature data since 1850.

to be significant for the temperature data, and also for the tree ring series since 1800. However, the tree ring series, some of which date back to BC3400 appear stationary without any evidence for a significant time trend. Our conclusions are mixed, but do not tend to be suggestive of the global warming phenomenon.

Finally, we also note in passing that there appear to be subtle differences between the natural, unadjusted tree ring series, and tree ring data in index form, which are adjusted for trends induced by the aging of trees in a cohort of trees. This latter measure is the one that is invariably used by dendrochronologists and researchers trying to reconstruct past climatic conditions. While both types of series exhibit long memory characteristics, the unadjusted tree ring data also possess significant ARCH effects with tranquil and volatile periods frequently lasting twenty or thirty years. Our analysis of one such series suggests that the adjustment procedure favored by dendrchronologists may well change some important characteristics of the series and may result in a series that less well correlated with the available, relatively recent temperature data.

II. The Temperature Data

Six different annual temperature series were used by Seater (1993). Three of the series are from the studies by JWW and are measured from 1854 through 1989. The three series are average annual temperature for the Northern Hemisphere (JWWNH), the Southern Hemisphere (JWWSH) and the entire Globe (JWWG). Another three series obtained from HL are from 1880 through 1985 and are for the Northern Hemisphere (HLNH), the Southern Hemisphere (HLSH) and the entire Globe (HLG). The global series, JWWG and HLG are graphed in <Figure 2> along with three tree ring series to be described later.

Seater (1993) provides further description of the nature and limitations of these series. After conducting a number of Dickey-Fuller unit root tests, Seater (1993, p. 269), notes that "both the HL and JWW data appear to be stationary," that the first differenced series "suggests over-differencing."[2] Consequently in subsequent analysis Seater (1993) deals with the levels of the temperature data and since the autocorrelations of the series are quite persistent, is led to estimate quite high order ARMA(11, 2) models with quadratic trend terms.

Ⅲ. Univariate Fractionally Integrated Models for Temperature

The above described characteristics of the temperature series are consistent with the Hurst Effect, where a time series has "long memory," in the sense that its autocovariance function γ_k, at large lag k, is

2) Diebold and Rudebusch (1991) and Hassler and Wolters (1994) examine the related problem of evaluating by simulation the power performance of the Dickey-Fuller unit root test when the true data generating process is either fractionally integrated white noise or an AR(1) processes. They show that the Dickey-Fuller test performs relatively poorly in distinguishing between the I(1) null hypothesis and the I(d) alternative.

$\gamma_k \approx \Xi(k)k^{2H-2}$ where $\approx$ denotes approximate equality, and $\Xi(k)$ is any slowly varying function at infinity and H is the Hurst coefficient, and $0<H<1$. Hence the Hurst effect concerns the phenomenon of very persistent, slowly decaying autocorrelations observed from a process which is nonetheless stationary. Hurst (1951) originally noted this effect in river flow data and Hurst (1957) used rescaled range analysis on 900 geophysical time series that appeared to exhibit this property.

A useful model in discrete time that is consistent with this phenomenon is the fractional unit root, or ARFIMA model of Granger (1980), Granger and Joyeux (1980) and Hosking (1981). The ARFIMA (p, d, q) model is,

$$\phi(L)(1-L)^d(y_t - \mu) = \theta(L)\varepsilon_t \tag{1}$$

where d denotes the fractional differencing parameter, all the roots of $\phi(L)$ and $\phi(L)$ lie outside the unit circle and $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon_s) = \sigma^2$, $E(\varepsilon_t \varepsilon_s) = 0$, for $t \neq s$. Then y_t will be covariance stationary and invertible for $-0.5 < d < 0.5$ and will be mean reverting for $d<1$.[3)]

The fractional model and its extensions have recently attracted considerable interest in econometrics and some recent developments and estimation techniques are described in Baillie (1996). An important issue concerns the reason for the prevalence of the Hurst effect in so many geophysical time series such as river flows and climatic data. Granger (1980) showed that the contemporaneous aggregation of many AR(1)

3) The corresponding infinite moving average representation weihts satisfy, $\Psi_j \approx c_1 j^{d-1}$, and the autocorrelations satisfy $\rho_j \approx c_2 j^{2d-1}$ for large j where c_1 and c_2 are constants.

processes with coefficients drawn from a beta distribution could be represented by fractional white noise. Recently Park (1995) has suggested a duration model where shocks to a system come from a certain distribution and there is a duration or survival time associated with each shock. Park (1995) shows that long memory processes can result from a particular survivor probability distribution.

The approach used in this study is to use a time domain approximate MLE based on Gaussian innovations which neglects initial observations. The properties of this type of estimator have been widely discussed in the literature and Baillie (1996) provides a survey of some of this work. Some largely favorable simulation evidence is presented by Baillie, Chung and Tieslau (1996). As noted by Li and McLeod (1986) the MLE for the stationary and invertible ARFIMA(p, d, q) model without an intercept are $T^{\frac{1}{2}}$ consistent and asymptotically normal. With a non-zero intercept the properties of the parameter estimates are unchanged except that the MLE of μ is $T^{\frac{1}{2}-d}$ consistent. Dahlhaus (1988, 1989) and Moehring (1990) provide detailed treatments of this case. If the parameter vector is denoted by λ, with first element μ, then

$$D_T(\hat{\lambda} - \lambda_0) \rightarrow N[0, \{D_T^{-1} A(\lambda_0)^{-1} B(\lambda_0) A(\lambda_0) D_T^{-1}\}^{-1}] \qquad (2)$$

where diag $D_T = [T^{\frac{1}{2}-d}, T^{\frac{1}{2}}, \cdots, T^{\frac{1}{2}}]$ and $A(.)$ represents the Hessian evaluated at the true parameter values λ_0. Under fairly general departures from normality the Gaussian density can still be maximized and inference based on QMLE. On denoting $B(.)$ as the outer product gradient, also evaluated at the true parameter values λ_0, and with μ

unknown, the QMLE of the parameter estimates have a limiting distribution of,

$$D_T(\hat{\lambda} - \lambda_0) \rightarrow N[0, \{D_T^{-1} A(\lambda_0)^{-1} B(\lambda_0) A(\lambda_0) D_T^{-1}\}^{-1}] \quad (3)$$

The simplest model within this class is fractional white noise, i.e., an ARFIMA(0, d, 0) process, $(1-L)^d(y_t - \mu) = \varepsilon_t$.

From a policy perspective, a central issue in this area of research concerns the magnitude and significance of any time trend. As noted by Seater (1993), most statistical methods are likely to find a significant, positive trend in the last hundred years of temperature data. Hence the following model involving fractional behavior around a trend stationary temperature process was considered,

$$(1 - L)^d(y_t - \mu - at) = \varepsilon_t \quad (4)$$

where $\varepsilon_t \sim$ NID $(0, \sigma^2)$, but subsequent inference is robustified. On denoting the vector of parameters as $\lambda'(d\mu a\sigma^2)$ it is shown in Chung (1997) that under the following normalization of D_T, where

$$\mathrm{diag}(D_T) = [T^{\frac{1}{2}}, T^{\frac{1}{2}-d}, T^{\frac{3}{2}-d}, T^{\frac{1}{2}}] \quad (5)$$

This result can readily by extended to the stationary and invertible TS-ARFIMA(p, d, q) process, $\phi(L)(1-L)^d(y_t - \mu - at) = \omega(L)\varepsilon_t$, with $\lambda' = (d\mu a\phi_1 \cdots \phi_p\theta_1 \cdots \theta_q\sigma^2)$, being $(p+q+4)$ in dimension, and diag $(D_T) = [T^{\frac{1}{2}}, T^{\frac{1}{2}-d}, T^{\frac{3}{2}-d}, T^{\frac{1}{2}}, T^{\frac{1}{2}}, \cdots, T^{\frac{1}{2}}]$.[4)]

〈Table 1〉 Estimation of Univariate Trend Sationary-ARFIMA(0, *d*, 0) Models for Temperature

	HL			JWW		
	Global	Northern	Sourthern	Global	Northern	Southern
μ	-0.427	-0.490	-0.299	-0.384	-0.377	-0.416
	(0.072)	(0.090)	(0.050)	(0.062)	(0.066)	(0.062)
a	0.005	0.006	0.004	0.004	0.004	0.004
	(0.001)	(0.002)	(0.0008)	(0.0007)	(0.0008)	(0.0007)
d	0.383	0.399	0.246	0.331	0.303	0.321
	(0.084)	(0.081)	(0.095)	(0.079)	(0.074)	(0.079)
σ^2	0.015	0.024	0.014	0.014	0.020	0.014
$\log L$	70.55	50.91	74.20	97.38	72.67	96.25
$Q(10)$	8.87	9.25	5.26	7.79	16.49	5.02
$Q^2(10)$	3.53	9.08	13.30	4.92	7.58	6.56
m_3	-0.22	-0.20	-0.13	0.16	-0.04	0.02
m_4	2.79	2.64	2.93	2.69	2.97	2.54

Model : $(1-L)^d(y_t - \mu - at) = \varepsilon_t,\ \varepsilon_t \sim \mathrm{NID}(0, \sigma^2)$

Key : Standard errors are given below corresponding parameter estimates. $\log L$ is the maximized value of the log likelihood, $Q(10)$ and $Q^2(10)$ are the Box-Pierce Portmanteau statistics calculated from 10 residual autocorrelations for level and squared residuals, respectively, while m_3 and m_4 are the sample skewness and kurtosis of the standardized residuals respectively.

4) The performance of the MLE applied to the trend stationary-ARFIMA(0, *d*, 0) model was assessed by detailed Monte Carlo simulations; see Chung (1997). The really important aspect concerns the small sample bias of the MLE of the long memory parameter, *d*; which has substantial bias for the smallest sample size of $T = 100$. The problem is exacerbated by d being 0.45 rather than 0.25 and is very similar to the results found by others for the estimation of pure ARFIMA(p, d, q) models. Hence it seems necessary to have a sample size of at least 500 to avoid problems with parameter estimation bias.

After some experimentation it was found that the univariate trend stationary, i.e., the TS-ARFIMA(0, d, 0) model was the most appropriate model for the six annual temperature series. Likelihood ratio tests of estimating TS-ARFIMA(p, d, 0) models $p = 1, 2, \cdots, 10$ and TS-ARFIMA(p, d, q) models for p and $q = 1, 2, 3$ failed to reject the simple TS-ARFIMA(0, d, 0) specification. These results were also confirmed by the AIC. The details of the estimated models are reported in <Table 1>. In general, the impact of the trend term is found to confirm Seater's findings and also provide more precise estimates of the trend and long memory parameters with tighter standard errors than those obtained from ARMA model estimation. <Table 1> also presents the Box-Pierce test statistic $Q^2(k)$ based on the squared residuals. Under the null hypothesis of conditional homoscedasticity, the statistic $Q^2(k)$ will have an asymptotic chi-squared distribution with k df. The null hypothesis can not be decisively rejected for all HL and JWW series. Hence there is no evidence that measured temperature series exhibit considerable volatility and ARCH effects.

Ⅳ. Multivariate Fractionally Integrated Models for Temperature

While specification analysis on the individual temperature series does not reveal any evidence of mis-specification; the cross correlations of the residuals from the univariate ARFIMA(0, d, 0) models reveal substantial contemporaneous correlation. For example the contemporaneous cross correlation between JWW global and northern hemisphere series is 0.89, the corresponding correlation between JWW global and southern hemisphere is 0.84 and the correlation between the northern and southern hemisphere is 0.53. This is in marked contrast to analysis of the lagged cross correlations, since there is no evidence significant correlation between any of the lagged residuals.

A possible model simplification occurs here if the temperature series are fractionally cointegrated. On applying the usual cointegration tests of Phillips and Perron (1988), and Kwiatkowski *et al.* (1992), the hypothesis of no cointegration could not be rejected. It seems that although highly correlated the individual temperature series do contain important and distinct information.

One model that appears to be appropriate for the temperature series, is the multivariate ARFIMA(p, d, q) model,

$$A(L)G(L)(Y_t - \mu - at) = B(L)\varepsilon_t \tag{6}$$

where $Y_t = (y_{1t}, y_{2t}, \cdots, y_{gt})$ is a vector of the g temperature of tree ring series. Similarly, $\mu' = (\mu_1 \cdots \mu_g)$, $\alpha' = (\alpha_1 \cdots \alpha_g)$, $\varepsilon_t \sim NID(0, \Omega)$, with Ω symmetric and positive definite, while $A(L)$ and $B(L)$ are both gxg matrices with typical elements being polynomials in the lag operator of orders p and q respectively, and $G(L)$ is a diagonal matrix with (i, i) element given by $(1-L)^{d_i}$. While the general MVARFIMA model is profligately parameterized, the set of temperature series considered in this study turns out to have a particularly simple structure. A set of seemingly unrelated ARFIMA models are obtained with $A(L) = B(L) = I_g$, and (6) reduces to

〈Table 2〉 Estimation of Unrestricted Multivariate Trend Stationary-ARFIMA(0, *d*, 0) Models for Temperature

	HL			JWW		
	Global	Northern	Sourthern	Global	Northern	Southern
μ	-0.387	-0.445	-0.238	-0.410	-0.389	-0.438
	(0.084)	(0.098)	(0.094)	(0.046)	(0.056)	(0.047)
α_i	0.005	0.006	0.004	0.004	0.004	0.004
	(0.001)	(0.002)	(0.001)	(0.0006)	(0.0007)	(0.0006)
d_i	0.368	0.371	0.378	0.242	0.253	0.256
	(0.050)	(0.052)	(0.057)	(0.045)	(0.047)	(0.049)
$\log L$	511.23			549.31		
$Q(10)$	8.55	8.95	5.19	8.41	16.55	5.17
m_3	-0.20	-0.16	-0.13	0.22	-0.02	0.10
m_4	2.80	2.63	2.87	2.80	2.98	2.53
λ_{LR}	633.90			568.62		

Model : $G(L)(Y_t - \mu - \alpha t) = \varepsilon_t$, where $\varepsilon_t \sim$ NID$(0, \Omega)$ and $G(L)$ is a g dimensional identity matrix $(1-L)^d I_g$, where I_g is a g dimensional diagonal matrix.

key : The above table provides details on the approximate MLE of two separate multivariate ARFIMA(0, *d*, 0) models : one for the three HL series, and the other for the three JWW series. For each model $g = 3$.

The LR statistics of whether the covariance matrix is diagonal.

$$\lambda_{LR} = T\left[\sum_g \ln(s_g^2) - \ln\left|\widehat{\Sigma}\right|\right]$$

where $s_g^2 = \hat{\varepsilon}_g' \hat{\varepsilon}_g / T$ from the individual ARFIMA(0, *d*, 0) regressions and $\widehat{\Sigma}$ is the maximum likelihood estimate of Σ. The LR statistic is aymptotically distributed as chi-squared with $g(g-1)/2$ degrees of freedom. The 1% and 5% critical values are 11.34 and 7.82, respectively. All other information is as for <Table 1>.

〈Table 3〉 Estimation of Restricted Multivariate Trend Stationary-ARFIMA(0, *d*, 0) Models for Temperature

	HL			JWW		
	Global	Northern	Sourthern	Global	Northern	Southern
μ_i	-0.426	-0.486	-0.279	-0.403	-0.386	-0.436
	(0.068)	(0.083)	(0.067)	(0.047)	(0.056)	(0.048)
α_i	0.006	0.006	0.004	0.004	0.004	0.004
	(0.001)	(0.001)	(0.001)	(0.0006)	(0.0007)	(0.0006)
d	0.364	0.364	0.364	0.250	0.250	0.250
	(0.050)	(0.050)	(0.050)	(0.044)	(0.004)	(0.044)
$\log L$	510.87			548.54		
$Q(10)$	8.70	9.16	5.66	8.43	16.59	5.29
m_3	-0.22	-0.19	-0.11	0.21	-0.02	0.10
m_4	2.80	2.64	2.85	2.79	2.97	2.51
λ_{LR1}	0.72			1.53		
λ_{LR2}	632.06			567.06		

Model : $G(L)(Y_t - \mu - \alpha t) = \varepsilon_t$, where $\varepsilon_t \sim \text{NID}(0, \Omega)$ and $G(L) = (1-L)^{d_i}$ where i is the g dimensional identity matrix.

key : As for <Table 2>, except that λ_{LR1} is the likelihood ratio test statistic for the $d_i = d$ for all $i = 1, 2$ and 3. Under the null hypothesis λ_{LR1} will have an asymptotic chi-squared distribution with $g(=3)$ degrees of freedom. The statistic λ_{LR2} is again a test for diagonality of Ω, as was λ_{LR} in <Table 2>. LR statistics of whether homogeneity on parmeters holds. $\lambda_{LR1} = -2(\ln L_r - \ln L_u)$, where $\ln L_r$ is the maximized log-likelihood for restricted model and $\ln L_u$ is the maximized log-likelihood for unrestricted model. The LR statistic is asymptotically distributed as chi-squared with the degrees of freedom equal to the number of restrictions. Since we have 3 degrees of freedom, the 1% and 5% critical values are 11.34 and 7.82 respectively.

$$G(L)(Y_t - \mu - \alpha t) = \varepsilon_t \tag{7}$$

where,

$$diag[G(L)] = [(1-L)^{d_1}(1-L)^{d_2} \cdots (1-L)^{d_t}]$$

The motivation for this model is analogous to that of Zellner's (1962) SURE system with (macro) shocks each year being common to all the temperature series. Hence omitted variables, (e.g. sunspots) or shocks that produce higher (lower) than normal annual temperatures throughout the world will affect the temperatures in the northern, southern hemispheres and globally in a similar manner. The seemingly unrelated fractional white noise model has a log likelihood of the form,

$$\begin{aligned} \ell(\lambda) = & -\left(\frac{GT}{2}\right)\ln(2\pi) - \left(\frac{T}{2}\right)\ln|\Omega| \\ & -\left(\frac{1}{2}\right)\sum \varepsilon_t' \Omega^{-1} \varepsilon_t \end{aligned} \tag{8}$$

Approximate MLE were obtained by numerically maximizing the above quantity and the results of estimating these TS-ARFIMA(0, d, 0) multivariate models are reported in <Table 2> and <Table 3>. Hence, the univariate estimations reported in <Table 1> can be regarded as the system of equations in (7) with the further restriction that Ω is diagonal. The LR test for this hypothesis for the HL set of three series is 638.17 and for the JWW series is 583.52. When compared with the asymptotic chi squared distribution with 3 degrees of freedom, this represents overwhelming rejection of the diagonality restriction. Hence there is substantial support for estimating the ARFIMA models simultaneously.

Analogously to the univariate analysis reported earlier, a range of diagonostic tests based on LR tests of higher order TS-ARFIMA (p, d, q) models were estimated. For both systems of temperature series, the hypothesis that $A(L) = B(L) = I_g$, could not be rejected. The estimates of the long memory parameter, d_i, are close across locations and a hypothesis of interest is that all three locations have the same underlying long memory characteristics. This assumption leads to the further simplification of the model in (7), so that the assumption of an identical long memory parameter across locations, implies that $D(L) = (1-L)^d I_g$. The model then reduces to the seemingly unrelated fractional white noise model,

$$(1-L)^d I_g(y_t - \mu - \alpha t) = \varepsilon_t \tag{9}$$

where $E(\varepsilon_t \varepsilon_s') = \Omega$ and is non-diagonal, while $E(\varepsilon_t \varepsilon_s') = 0$ for $s \neq t$.

The results are presented in <Table 3> and the LR tests of a common long memory parameter across locations are 0.72 for the HL series and 1.53 for the JWW series. Hence, for neither system of temperature data can the hypothesis of the same long memory parameter be rejected across regions. The estimate of d from the HL data is 0.364, and for the JWW data is 0.250; in both cases the asymptotic t statistic for $d = 0$, exceed 6. Hence, surprisingly simple long memory models are found to be adequate across the different temperature series. The estimate of the trend parameter is quite similar to that of the univariate analysis.

V. Analysis of Tree Ring Series

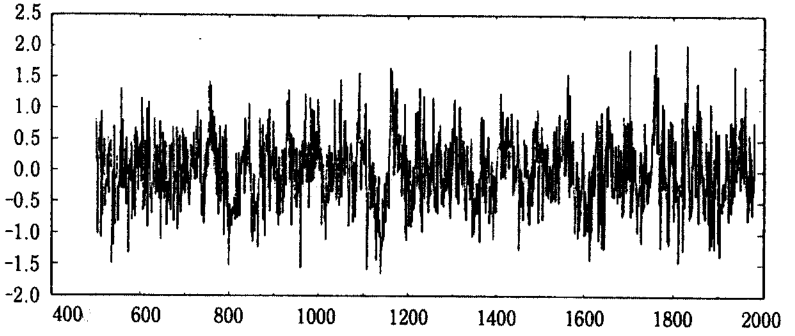
Four tree ring series were chosen to analyze alongside the temperature data. The Campito series is the annual width of tree rings from a sample of Bristlecombe pine trees on Mount Campito, California. The series comprises a total of 5,405 annual observations from 3436BC through 1969AD. The series was collected by Valmore C LaMarche, now deceased, of the University of Arizona and given to Ian McLeod of the University of Western Ontario, who kindly made the data available to me.

The second series, Trier, are the annual width of a sample of oak trees outside the town of Trier on the west bank of the Rhine in Germany. There are 1,481 observations from 822AD through 1964 and are given in Lamb (1977). Lamb reports that for most years the tree ring width was the sample mean of a sample of between 10 and 36 trees; while the sample size was only between 1 and 9 for the years before 910 and the sample size was between 4 and 8 for the years between 1060 and 1129.

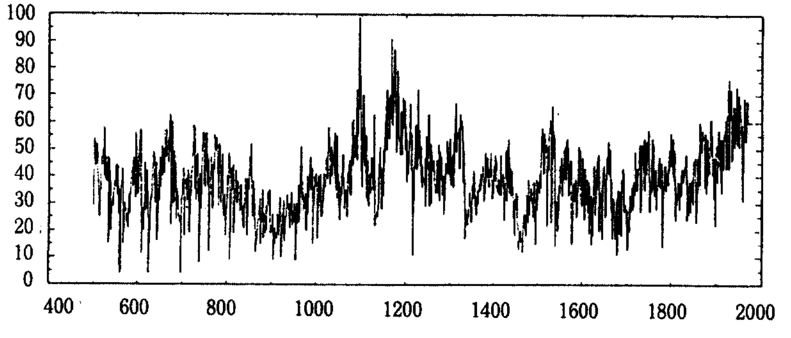
The third tree ring series is Tree. Br, which is obtainable from Briffa *et al.* (1990) and are summer temperature reconstructions from tree rings in northern Scandinavia from 500AD through 1980. The three tree ring series are graphed in <Figure 2> from 500AD though 1980, and are also plotted in <Figure 1> from 1854 through 1985 alongside two temperature series. The Tree. Br series was also analyzed by Seater (1993). While the Campito and Trier data reflect raw, unadjusted measurements of a sample of tree ring widths; the Br data are adjusted to "reconstruct"

〈Figure 1〉 Tree Rings Series of Width or Index from 500 to 1980: Br-Campito-Trier

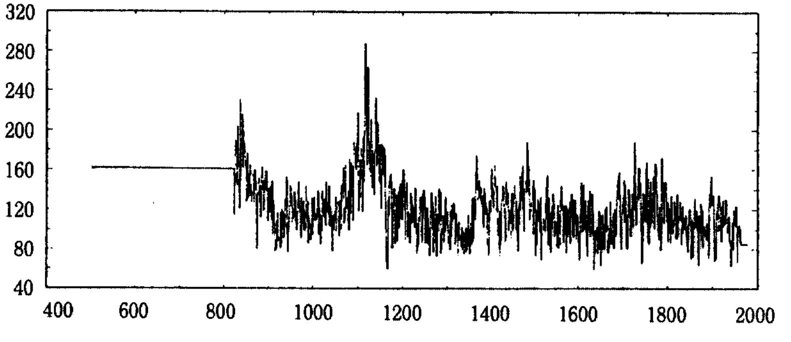
(a) Br Tree Ring Series of Index



(b) Campito Tree Ring Series of Width

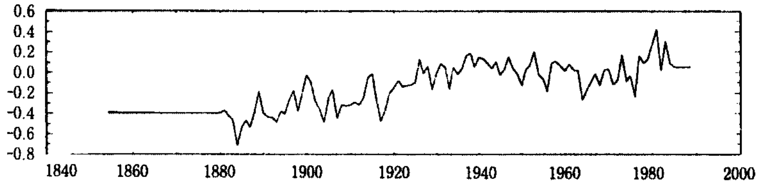


(c) Trier Oak Tree Ring Series of Width

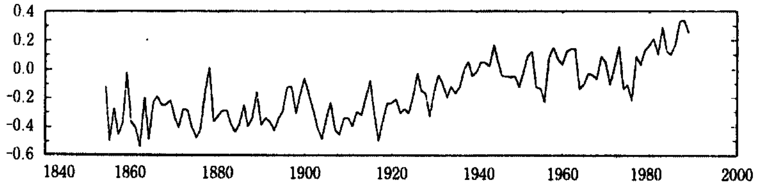


⟨Figure 2⟩ Temperature and Tree Ring Series of Width or Index from 1854 to 1989

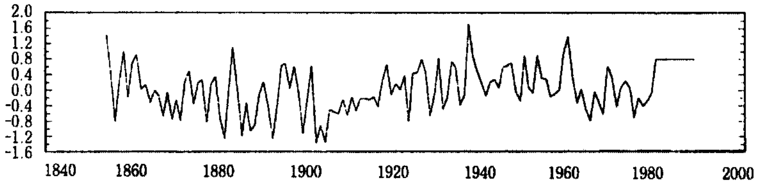
(a) HIG Temperature Series



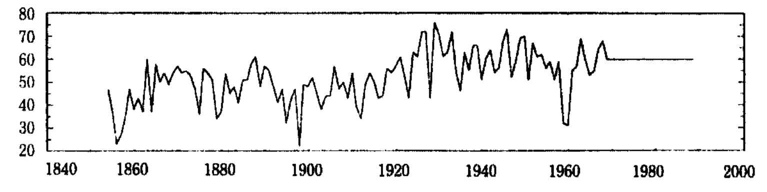
(b) JWWG Temperature Series



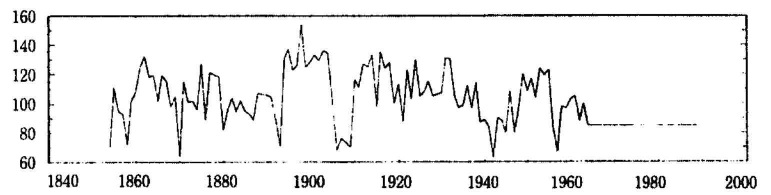
(c) Br Tree Ring Series



(d) Campito Tree Ring Series



(e) Trier Oak Tree Ring Series



previous climatic conditions. The science of dendrochronology emphasizes temperature and water stress as determining tree ring growth. As described by Fritts (1976), little water stress and high temperature are believed to positively influence tree ring growth, while high temperature combined with low water stress can reduce tree ring growth, since water loss from the leaves is increased. As noted by Seater (1993) a known "statistical deficiency" of the Briffa *et al.* data concerns the adjustments to the tree ring series. In particular, if TR_t is the width of tree rings in year t, and MX is the maximum latewood density of the type of tree; then the unobserved temperature, T_t, in year t is reconstructed from the formula, $T_t = .081TR_t + .109TR_{t+1} + .600MX_t + .052MX_{t+1}$.

The fourth series, CA046, is taken from a sample of tree ring data provided by the National Geophysical Data Center at Boulder, Colorado). Series CA046 one of many such series and was chosen for this study on the basis of its length and lack of missing observations. All the series at the National Geophysical Data Center are adjusted and are produced in an index number from where the width of tree rings series is divided by a trend estimate obtained from fitting a polynomial function of time to the width of tree ring series. Schweingruber (1988), Cook and Kairiukstis (1990) describe the technique in detail. Such indices are designed to adjust for the increasing age of the tree(s), but can also have the undesirable effect of removing long-term climatic changes. Hence the smoothed tree ring series are designed to reduce variation in the tree ring series, but may also substantially reduce the quality of the information in the tree ring series concerning past climatic conditions.

Tests of long memory effects and experimentation with various

〈Table 4〉 Estimation of ARFIMA(0, d, 2)-FIGARCH(1, ∂, 1) Models for Tree Ring Width and Index Series

	Br	Campito			Trier		
	(0, d, 0)	(0, d, 0)	(0, d, 0) -(1, 1)	(0, d, 0) -(1, ∂, 1)	(0, d, 2)	(0, d, 2) -(1, 1)	(0, d, 2) -(1, ∂, 0)
μ	0.040	46.864	37.412	35.959	1.385	1.186	1.215
	(0.120)	(3.541)	(3.694)	(4.559)	(0.131)	(0.134)	(0.145)
d	0.324	0.450	0.444	0.452	0.470	0.412	0.422
	(0.022)	(0.012)	(0.012)	(0.013)	(0.060)	(0.061)	(0.064)
θ_1	-	-	-	-	0.138	0.105	0.125
					(0.071)	(0.068)	(0.070)
θ_2	-	-	-	-	-0.088	-0.117	-0.019
					(0.045)	(0.044)	(0.045)
∂	-	-	-	0.254	-	-	0.167
				(0.055)			(0.051)
ω	0.261	63.954	1.074	3.365	0.042	0.0009	0.011
	(0.010)	(1.709)	(0.427)	(1.200)	(0.002)	(0.0004)	(0.004)
a	-	-	0.034	-	-	0.043	-
			(0.007)			(0.012)	
β_1	-	-	0.950	0.766	-	0.936	0.086
			(0.012)	(0.049)		(0.017)	(0.067)
ϕ_1	-	-	-	0.633	-	-	-
				(0.066)			
$\log L$	-1107.41	-18906.9	-18802.8	-18795.1	190.12	220.69	216.07
T	1481	5405	5405	5405	1143	1143	1143
$Q(20)$	33.41	21.57	21.72	21.53	14.91	15.23	16.13
$Q^2(20)$	23.79	238.79	34.36	15.73	197.65	24.87	32.45
m_3	-0.03	-0.63	-0.60	-0.66	0.08	0.00	-0.00
m_4	3.19	4.56	4.42	4.56	3.76	3.07	3.24

Model : $(1-L)^d(y_t-\mu) = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2}$

$\varepsilon_t = z_t\sigma_t$ where z_t is i.i.d. with $E(z_t)=0$ and $var(z_t)=1$

$\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \{1-\beta_1L-(1-\phi_1L)(1-L)^{\partial}\}\varepsilon_t^2$

key : Standard errors are given below corresponding parameter estimates. Log L is the maximized value of the log likelihood, and $Q(20)$ and $Q^2(20)$ are the Ljung-Box Portmanteau statistics calculated from 20 residual autocorrelations, while m_3 and m_4 are the sample skewness and kurtosis of the standardized residuals respectively.

univariate models were implemented on the various tree ring series. The most appropriate estimated models are reported in <Table 4>. Various fractionally integrated univariate are remarkably successful in representing very long series of tree ring widths, which are often used as a proxy for temperature. <Table 4> also presents the Ljung-Box test statistic $Q^2(k)$ based on the squared residuals. Under the null hypothesis of conditional homoscedasticity, the statistic $Q^2(k)$ will have an asymptotic chi-squared distribution with k df. The null hypothesis can be decisively rejected for Campito and Trier tree ring series, while $Q^2(20)$ is not significant even at the .05 level for Br tree ring series.

Consequently, ARFIMA$(0, d, 2)$-FIGARCH$(1, \partial, 1)$ models were estimated for the Tree. Br, Mount Campito bristlecone pine series and the Trier oak trees. The model is then of the form,

$$
\begin{aligned}
(l-L)^d(y_t-\mu) &= (1-\theta_1 L-\theta_1 L^2)\varepsilon_t \\
\sigma_t^2 &= \omega+\beta_1\sigma_{t-1}^2+\{1-\beta_1 L-(1-\phi_1 L)(1-L)^{\partial}\}\varepsilon_t^2
\end{aligned}
\tag{10}
$$

where $\varepsilon_t = z_t\sigma_t$, where z_t is $i.i.d.(0,1)$ process, σ_t^2 a time-varying, positive and measurable function of the information set at time $t-1$. Hence, $\sigma_t^2 = \omega/[1-\beta(1)] + \lambda(L)\varepsilon_t^2$, where $\lambda(L) = \{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^{\partial}\}$. For large lag k, the impulse responses are $\lambda_k = ck^{d-1}$, which generates slow hyperbolic rate of decay on the impulse response weights of the conditional variance σ_t^2. The maximum likelihood estimates of the GARCH parameters in <Table 4> are extremely similar across tree ring series with the estimated value of $(\alpha+\beta_1)$ being close to unity. This indicates the possible existence of a

⟨Table 5⟩ Estimation of Trend Stationary ARFIMA(0, d, 2)-FIGARCH (1, ∂, 1) Models for Tree Ring Width and Index Series

	Br	Campito			Trier		
	(0, d, 0)	(0, d, 0)	(0, d, 0) -(1, 1)	(0, d, 0) -(1, ∂, 1)	(0, d, 2)	(0, d, 2) -(1, 1)	(0, d, 2) -(1, ∂, 1)
μ	0.057	50.481	44.890	46.499	1.484	1.350	1.370
	(0.172)	(3.375)	(5.943)	(6.002)	(0.112)	(0.127)	(0.128)
α	-0.00029	-0.0018	-0.0034	-0.0033	-0.0004	-0.0004	-0.0004
	(0.0002)	(0.0016)	(0.0018)	(0.0018)	(0.0002)	(0.0002)	(0.0002)
d	0.324	0.448	0.443	0.452	0.439	0.391	0.398
	(0.022)	(0.012)	(0.012)	(0.012)	(0.057)	(0.051)	(0.052)
θ_1	-	-	-	-	0.110	0.091	0.106
					(0.069)	(0.060)	(0.061)
θ_2	-	-	-	-	-0.099	-0.021	-0.114
					(0.044)	(0.041)	(0.042)
∂	-	-	-	0.254	-	-	0.180
				(0.056)			(0.054)
ω	0.261	63.929	1.088	3.401	0.042	0.00084	0.00992
	(0.010)	(1.703)	(0.440)	(1.233)	(0.002)	(0.0004)	(0.0038)
α	-	-	0.035	-	-	0.043	-
			(0.007)			(0.012)	
β_1	-	-	0.948	0.761	-	0.936	0.107
			(0.012)	(0.051)		(0.017)	(0.072)
ϕ_1	-	-	-	0.630	-	-	-
				(0.067)			
$\log L$	-1107.40	18905.77	-18800.01	-18792.66	192.44	224.03	219.53
T	1481	5405	5405	5405	1143	1143	1143
$Q(20)$	33.41	21.37	21.41	21.28	14.19	15.12	16.10
$Q^2(20)$	23.70	244.99	34.18	16.12	202.91	20.83	27.14
m_3	-0.01	-0.59	-0.56	-0.63	0.21	0.11	0.11
m_4	3.19	4.82	4.37	4.52	3.83	3.09	3.16

Model : $(1-L)^d(y_t-\mu-\alpha t)=\varepsilon_t+\theta_1\varepsilon_{t-1}+\theta_2\varepsilon_{t-2}$

$\varepsilon_t=z_t\sigma_t$ where z_t is i.i.d. with $E(z_t)=0$ and $var(z_t)=1$

$\sigma_t^2=\omega+\beta_1\sigma_{t-1}^2+\{1-\beta_1L-(1-\phi_1L)(1-L)^{\partial}\}\varepsilon_t^2$

key : As for <Table 4>.

⟨Table 6⟩ Estimation of Trend Stationary ARFIMA(0, *d*, 0) Models for Ring Series

		1800-	1854-	1880-
μ	Br	-0.068(0.220)	-0.015(0.215)	-0.346(0.207)
	Campito	39.565(4.443)	42.036(3.703)	44.742(3.895)
	Trier	110.933(6.560)	100.398(10.219)	99.102(11.878)
	CA046	8.941(0.955)	10.561(0.479)	11.358(0.470)
α	Br	0.022(0.022)	0.001(0.003)	0.006(0.003)
	Campito	0.116(0.042)	0.164(0.052)	0.187(0.071)
	Trier	-0.058(0.066)	0.009(0.146)	-0.008(0.217)
	CA046	0.043(0.009)	0.052(0.007)	0.061(0.009)
d	Br	0.265(0.065)	0.201(0.079)	0.196(0.091)
	Campito	0.341(0.065)	0.255(0.078)	0.248(0.088)
	Trier	0.276(0.073)	0.375(0.093)	0.463(0.108)
	CA046	0.329(0.061)	0.094(0.082)	0.062(0.098)
ω	Br	0.331(0.035)	0.331(0.042)	0.320(0.045)
	Campito	70.765(7.652)	80.590(10.537)	80.728(11.968)
	Trier	267.139(29.412)	291.510(39.130)	276.630(42.433)
	CA046	3.502(0.379)	3.558(0.465)	3.382(0.501)
T	Br	181	127	101
	Campito	171	117	91
	Trier	165	111	85
	CA046	171	117	91
$\log L$	Br	-156.67	-110.02	-85.74
	Campito	-606.80	-422.80	-328.92
	Trier	-695.11	-472.47	-359.57
	CA046	-349.81	-240.26	-184.56
LM	Br	12.55	8.36	6.14
	Campito	4.54	7.43	8.95
	Trier	8.21	6.78	6.81
	CA046	5.45	4.12	5.85
$Q(10)$	Br	17.67	23.84	16.57
	Campito	9.22	7.90	7.32
	Trier	18.56	12.88	6.23
	CA046	15.92	10.56	10.57
$Q^2(10)$	Br	17.68	12.74	10.18
	Campito	5.49	7.71	8.77
	Trier	8.09	7.18	6.82
	CA046	5.81	2.77	4.15
m_3	Br	0.22	0.15	0.27
	Campito	-0.47	-0.51	-0.57
	Trier	-0.24	-0.20	-0.02
	CA046	-0.05	-0.12	-0.16
m_4	Br	3.27	3.06	3.04
	Campito	3.39	3.39	3.57
	Trier	2.75	2.73	2.93
	CA046	2.60	2.68	2.62

key : As for <Table 1>.

fractionally integrated GARCH process.

It should be noted that the statistically significant positive trend coefficients may well be due to small sample sizes; i.e., due to temperature series. We therefore need to check whether there is a time trend in tree ring series. The maximum likelihood estimates for the parameters in (10) with trend term are given in <Table 5>. In particular, it was found that the hypothesis that $\delta=0$ could not be rejected for Br and Campito tree ring series, while it is significant at the .05 level for Trier series. Hence, there was no apparent evidence of global warming over the entire history of these series.

For all the tree ring series models reported in <Table 6>, the long memory parameter, d is highly significant different to zero and is slightly higher than the estimates of d obtained for the temperature data.

Estimates of TS-ARFIMA(0, d, 0) models for tree rings estimated over the period of time when the world' s economic activity and emissions of green house gasses have increased. Three separate sub samples were chosen, staring from 1800, 1854 and 1880 until the end of the sample. The Campito and CA046 series have positive trend coefficients, which are significantly different from zero for all three sub-periods. The trend coefficient is always positive for the Br series, but is only significant since 1880. While the parameter associated with time trend is not significantly different from zero for the Trier series.

Ⅵ. Concluding Remarks

The correlation between the Br series and measured temperature between 1876 and 1950 is about .50 and was previously analyzed by Seater (1993) who estimated an AR(17) around a linear time trend. Interestingly, Seater (1993) found the time trend coefficient to be negative and insignificant over the periods of 1880 through 1980. Some of the unadjusted tree ring series displayed long memory volatility behavior and consequently ARFIMA-FIGARCH models were estimated in <Table 5>. The FIGARCH model is described in detail by Baillie, Bollerslev and Mikkelsen (1996) and again estimation is performed by QMLE.

However, very long series of observations on the width of tree rings, which are often used as a proxy for temperature are also extremely well described by fractionally integrated models. However, there is no apparent evidence of a significant time trend superimposed on the long memory behavior for the long records, sometimes in excess of 1,000 years, for the tree ring records. Analysis of very short records of tree ring series can also give rise to a significant estimate of the time trend parameter. This is also consistent with the estimation of a trend stationary ARFIMA model to data generated from a stationary fractionally integrated process. Hence, although it is hard to make strong conclusions on the basis of the last hundred years of temperature data; the series are consistent with being generated by a stationary, long memory process. The statistically significant trend coefficients may well be anomalous and due to small sample sizes.

These results cast some doubt on the basic assumption behind many current studies that the world's climates are definitely warming. The notion that human activity has caused the increase in world temperature over the last 150 years also seems inconsistent with the fact that the greatest recorded increase in temperature occurred between 1850 and 1925, while the greatest increase in greenhouse gas emissions occurred since 1925. Also, there is some more recent scientific evidence that satellite data of the upper atmosphere do not show much indication of increased temperature. Other work has suggested that temperature movements follow solar activity.

While it is important for policy makers to be aware of the possibility of climatic change, appealing to results obtained from relatively short series of annual temperature series does not seem to be appropriate. The long range cycles and Hurst effect in series related to temperature indicate the potential for making false conclusions from such short series. Further statistical analysis of the information contained in some of the long historical geophysical data appears worthwhile.

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ABSTRACT

Global Warming Trend : Further Evidence From Multivariate Long Memory Models of Temperature and Tree Ring Series

Sang-Kuck Chung

This paper shows that various fractionally integrated univariate and multivariate are remarkably successful in representing annual temperature series and also very long series of tree ring widths, which are often used as a proxy for temperature. The analysis also suggests that human recorded temperature series are not inconsistent with being generated by a stationary, long memory process. From the empirical results, we should be noted that the statistically significant positive trend coefficients may well be due to small sample sizes. These results cast some doubt on the basic assumption that global warming is definitely occurring.