Unit Roots in the Climate:

Is the Recent Warming Due to Persistent Shocks?

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ABSTRACT

In recent years, scientists have become increasingly certain that the rise in global mean temperature is due in part to rising concentrations of greenhouse gasses (GHGs). Evidence has come from two directions, observation of the climate and greenhouse gas concentrations (detection of the climate change fingerprint) and from computational models which use physical relationships (GCMs). However, as has often been pointed out, such work does not account for the possibility that the recent warming trend could be part of the natural long run cycles in the climate (as evidenced by ice ages which last for thousands of years). Such cycles have a statistical analog in the presence of near-unit roots. We find that a unit root in the temperature series cannot be rejected, and the forcing from greenhouse gas concentrations is very similar to a time trend. Hence there is the possibility that the temperature rise is due to long run cycles, and that the relationship between temperature and GHGs is spurious. However, when we adjust the data to account for the possibility of unit roots, the relationship between temperature and GHGs remains, indicating that previous findings are robust.

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I. Introduction

Scientists are increasingly certain that the rise in global temperatures over the last 140 years is due at least in part to increasing concentrations of greenhouse gasses (GHGs). The global mean temperature has risen by .7 degrees Celsius since 1860, when statistics were first kept. Over the same period, carbon dioxide (the leading GHG) concentrations have increased 46 percent.

There is now a wide body of literature attempting to pin down the relationship between GHGs and temperature. There are two main lines of work. The first uses relationships from physics to build a bottom up circulation model of the climate. These are often referred to as general circulation models (GCMs).[1] Other authors use reduced form statistical models, trying to detect a climate change fingerprint from observations of the atmospheric temperature and GHG level in order to validate the GCMs. Such work is important because until GCM models are validated by direct detection of the GHG effect, GCMs are open to doubts based incorrect specification of the model (Wigley and Barnett, 1990). In general, if a climate change fingerprint is clearly evident, there is a much stronger case for controlling the problem.

Additionally, researchers such as Kelly and Kolstad (1999) and Wigley and Barnett (1990) show that when the climate change fingerprint is detected has important policy consequences. If detection of the fingerprint in the near future is likely, a wait and see approach might be best. If detection is unlikely in the near term, an act now strategy is more preferable.

An important and uncertain parameter of GCMs is the climate sensitivity, which is the equilibrium temperature change per unit of the change in radiative forcing (heat radiated back to the earth). An alternative measure which is directly proportional to the climate sensitivity is the total equilibrium (steady state) temperature change from a doubling of GHGs. The climate sensitivity measures the long run effects of GHG emissions on temperature. Therefore, statistical models also focus on the equilibrium temperature change per unit of forcing, in order to validate

[1] See Cubasch and Cess (1990) for an overview.

the equilibrium temperature change found in GCMs. Although previous work on detection of the climate change fingerprint is extensive, such work on detection does not account for the possibility that the warming trend could be part of the natural long run cycles in the climate. For example, cold trends such as ice ages last for thousands of years. There is also evidence that the temperature has been significantly warmer (Folland, Karl, and Vinikov, 1990). Long run trends could be the result of "shocks" to the system, such as volcanoes or solar irradiation which affect the climate for centuries (Wigley and Barnet, 1990). The fact that GHG levels have increased over the past century could be just a coincidence. Accounting for such a possibility statistically requires unit root analysis, which has not been considered in the literature.

The purpose of this paper is to account for the possibility that the warming trend could be caused by persistent shocks and climate inertia. In fact we implicitly test the two competing hypothesis to explain the rise in temperature: radiative forcing from increases in GHG concentrations and persistent shocks and climate inertia. When we test the radiative forcing effect alone we find strong evidence that radiative forcing from GHGs explains temperature changes. The equilibrium temperature change is 1.27 degrees Celsius for a doubling of GHGs, and the standard error is only .083. We then test the hypothesis that shocks persist in the data, and cannot reject the hypothesis. However, when we correct for the possibility of persistent shocks, the evidence becomes only marginally less clear: the equilibrium temperature change estimate is 1.30 with a standard error of .173. Hence we can still reject the hypothesis that there is no GHG effect or that the equilibrium temperature change is zero.

We use unit root analysis to account for the possible presence of persistent shocks. The term unit root refers to the possibility that one or more coefficients in an autoregressive process are equal to one. In such a case shocks to the system persist forever. For example, if GDP follows a unit root process then centuries old shocks, such as the invention of the wheel, affect today's GDP.[2] In this case, there are difficulties drawing inference from standard regression

[2] Of course few shocks are ever truly permanent. Even the effect of the wheel on GDP may eventually die out if better technology is invented. However, a root which is close to one still poses an identical problem, given that our data set consists of only 140 observations.

techniques such as ordinary least squares. The problem manifests itself most often as a spurious regression. If both the dependent and independent variables are non-stationary, ordinary least squares is no longer asymptotically well-behaved.

We perform several unit root tests on both global mean temperature and in radiative forcing from GHG concentrations. We are unable to reject the hypothesis that there is a unit root in the global mean temperature at even the 90 percent level. We can reject the presence of a unit root in the radiative forcing with high confidence, however a time trend is highly significant. This indicates that the relationship between temperature and forcing may be spuriously precise because both variables are non-stationary. Although unit root tests frequently have low power, failure to reject (especially at such a low percent) indicates that one should account for the possible presence of unit roots. The problem can be corrected via first differencing or by using a robust estimation method such as fully-modified OLS (FM-OLS) or equivalently augmented least squares (ALS). Accordingly, we ran the modified regression of temperature and forcing using augmented least squares and found that while the standard error of the equilibrium temperature change does rise from .083 to .173, the 95 percent confidence lower bound is .954 degrees Celsius. Hence accounting for the presence of long run cycles in the climate does increase uncertainty, but the GHG effect is still strongly present in the data.

In the next section we review some related work. Section III develops a reduced form, but widely used temperature model and computes the implied equilibrium temperature change as a function of the estimated coefficients. In section IV we present the data along with alternative possibilities. In section V we show that standard estimation techniques implies a highly significant equilibrium temperature change. We then show that a unit root cannot be rejected in the temperature data. We then test for cointegration and consider the appropriate way to account for the presence of a unit root. The results indicate that ALS is most appropriate for our problem. Finally we re-estimate the model and show that using ALS, which is robust to the presence of unit roots, produces little change in the results. We conclude with some policy implications.

II. Related Work

Many researchers estimate the effects of GHGs on the climate through empirical data. These papers generally fall into the category of pure statistical models and hybrid approaches which estimate some parts of GCMs and calibrate other parts. For example, Bassett (1992) calculates the probability that the record global mean temperature recorded in 1988 will be broken. Bassett estimates various temperature statistical models of temperature, including a time trend, a constant model, and a time trend with first order autocorrelation and concludes that autocorrelation and time trends in temperature will likely result in further temperature records. Solow and Broadus (1989) also show that the non-stationarities in temperature could by themselves generate the recently observed high temperatures.

An example of the hybrid approach is Schlesinger and Ramankutty (1995), which simulates the Energy-balance climate/upwelling diffusion (EBC) GCM with white noise and perform spectral analysis on the simulated global mean temperature data to assess the likelihood that the observed 65-70 year oscillation in the temperature data is due to random variation in the climate. They reject the hypothesis.

Researchers also search for the climate change fingerprint using data obtained from climate sensitive phenomena. Climate sensitive phenomena include ice cores, tree rings, pollen remains, ocean sediments, and animal remains, all of which can be found over a long time span and vary with temperature in a relatively known way. Such data sets imply a history of both dramatically cooler periods (ice ages) and warmer periods, which last for hundreds or thousands of years. For example, the medieval warm period lasted from about 1000-1400 AD. Data on GHG concentrations is also available from several sites. Some warming periods show increased GHG concentrations, however, many do not. Statistical inference from such data is difficult due to the large number of differences between ancient periods and today, such as different topography, sun position, and ecology. Additionally, the dates of the data sets vary widely and are unavailable over large portions of the world. However, some researchers argue that some climate variations are the result of shocks to the climate such as volcanic eruptions or solar irradiance (see for example Hammer, 1977 and Porter, 1986). Folland, Karl, and Vinikov (1990) provides a survey of results.

The possibility that the observed warming trend is the result of shocks to the climate and climate inertia has an analogue in the statistics literature known as unit roots. In the context of regression analysis on time series, a key assumption of ordinary least squares is that the dependent and independent variables are stationary. If a unit root is present, a spurious regression may result. That is, the OLS estimate may appear spuriously precise as the covariance matrix grows faster than $\sqrt{T}$. Indeed Granger and Newbold (1974) simulated two unrelated random walks (a type of unit root) and were unable to reject the hypothesis that the random walks were related 75 percent of the time. Moreover, the regressions often had a high R^2. Hence a spurious regression occurred, with least squares indicating the independent variable had explanatory power when by construction it did not.

Since the work of Granger and Newbold (1974), many authors have devised techniques for correcting for unit roots. Hamilton (1994) and Enders (1995) suggest first differencing the data. After first differencing the data the estimated parameters change little, but there is no spurious regression problem assuming the first differenced data is stationary.

There are several situations where first differencing is not appropriate. First if the data truly is stationary, first differencing causes misspecification. Thus if the global mean temperature has a root near one, but not exactly equal to one first differencing results in misspecification. Second, if the data is cointegrated first differencing does not correct the problem. Finally, if the data is trend stationary then first differencing results in a misspecified moving-average model. We find evidence against cointegration on both theoretical and statistical grounds. First, on theoretical grounds the driving processes behind temperature and forcing from GHG concentrations are quite different. Shocks to temperature arise from solar irradiance variation and events such as volcanic eruptions. Shocks to GHG concentrations are primarily improvements in technology and changes in tastes and preferences for consumption goods which emit carbon dioxide. Further, forcing from GHGs behaves very similar to a time trend while temperature is best modeled by an autoregressive process, indicating different error structures. Hence we consider both first differencing and augmented least squares (ALS), which is robust to the presence of a near unit root as well as a unit root. We consider ALS to be the most appropriate, because while shocks to climate may last for an extremely long time, it is unlikely that shocks are truly permanent.

III. Temperature model and Equilibrium Temperature Change

Many climatic processes are stochastic. In particular, the average annual global temperature is well recognized to be stochastic, with some deterministic elements, such as radiative forcing from increased levels of greenhouse gases. Consider the simplest representation of this process:

$$T_t = \alpha_0 + u_t \tag{1a}$$

Here T_t is the annual global temperature (°C) difference of the upper ocean in year *t* from the 1961-1990 average temperature, α_0 is a constant, and u_t is a random shock, assumed to have a zero mean but perhaps exhibiting serial correlation. Bassett (1992) estimates several different stochastic processes for temperature of the form of equation (1a). For the case of first-order autocorrelation of the error term u_t, equation (1a) can be rewritten as:

$$T_t = \beta_0 + \beta_1 T_{t-1} + \varepsilon_t \tag{1b}$$

Here β_1 is a constant, ε_t exhibits no serial correlation and $\beta_0 = \alpha_0(1-\beta_1)$. Bassett (1992) estimates values of $\beta_1 = .808$ and Var(ε)=0.0185.

Our primary interest is in the effect of GHGs on the temperature process. Let M_t denote concentrations of GHGs in CO_2–equivalent gigatons (Gt), M_b be the pre-industrial concentration. The relationship between CO_2–equivalent GHG concentrations and temperature is well-approximated by a logarithmic approximation (see Shine, et. al. 1990 for details). Define the radiative forcing F_t (in watts per square meter) as:

$$F_t = \left(\frac{F_{2x}}{\ln(2)} \right) \ln \left[\frac{M_t}{M_b} \right] \qquad (2a)$$

Here $F_{2x} = 4.39$ is the radiative forcing for a doubling of CO_2 above the pre-industrial level M_b given in Shine et. al. (1990). Next let R_1 be the thermal capacity of the upper atmosphere and ocean, then:

$$T_t = \alpha_0 + \frac{1}{R_1} F_t + u_t \qquad (2b)$$

Hence we work with:

$$T_t = \alpha_0 + \alpha_1 F_t + u_t \qquad (2c)$$

Rather than considering α_1, scientists typically report the total equilibrium (steady state) temperature change from a unit increase in radiative forcing, known as the climate sensitivity (λ). Alternatively, researchers and policy makers often report the total equilibrium (steady state) temperature change from a doubling of greenhouse gasses above the pre-industrial level (M_b), known as T_{2x}. The climate sensitivity and T_{2x} are standard ways to interpret α_1. The climate sensitivity and the total equilibrium temperature change are related by $\lambda = \frac{T_{2x}}{F_{2x}}$.

Suppose first that u_t exhibits no serial correlation. Then clearly the total equilibrium temperature change is $T_{2x} = F_{2x}\alpha_1$ and the climate sensitivity is $\lambda = \alpha_1$. For the case of first order autocorrelation, we can rewrite equation (2c) as:

$$T_t = \beta_0 + \beta_1 T_{t-1} + \beta_2 (F_t - \beta_1 F_{t-1}) + \varepsilon_t \qquad (3a)$$

Given equation (3a), the climate sensitivity is identical to the previous specification. However, since forcing changes relatively slowly from year to year, we use the following approximation of equation (3a):

$$T_t = \beta_0 + \beta_1 T_{t-1} + \beta_2 F_t + \varepsilon_t \qquad (3b)$$

From equations (3b) and (2a), the total equilibrium temperature change from a doubling of GHGs above pre-industrial levels is:

$$T_{2x} = \frac{\beta_2}{1-\beta_1} F_{2x} \tag{4}$$

The climate sensitivity is thus:

$$\lambda = \frac{\beta_2}{1-\beta_1}$$

Similar calculations give the climate sensitivity and equilibrium temperature change for autocorrelation of order greater than one.

Of course we assume $\beta_1 < 1$ when calculating the equilibrium temperature change. In fact as β_1 nears one, a radiative forcing from GHGs affect the climate for longer and longer periods. In the limit, radiative forcing has permanent effects. From a policy perspective, obtaining a good statistical estimate of β_1 is very important. If β_1 is near one then forcing from GHGs is near irreversible, since even if all anthroprogenic GHG concentrations are removed, the climate does not revert back to the pre-industrial state. β_1 then represents the inertia of the climate.

IV. Data

According to general circulation models, a clear signal of climate change from emission of GHGs would be a general rise in atmospheric temperatures near the surface of the earth (Folland, Karl, and Vinnikov, 1990). Other changes such as temperature changes in more disaggregated areas, increased rainfall, higher sea levels, rising ocean temperatures may also indicate climate change from GHGs. Another possibility is to examine data derived from climate sensitive phenomena such as ice cores. Such data is often available for a longer time span, however, climate sensitive data is often location specific and possibly subject to more error. Data sets on rainfall, sea level, and ocean temperatures are less complete than the global temperature data. Global mean temperature data also shows a clearer pattern of climate change versus other data sets, indicating the best possible chance of detecting climate change. Finally, the global mean temperature is widely cited as evidence of climate change. Therefore, we focus on aggregated temperature data.

We use the data set of Folland, Karl, and Vinnikov (1990), which is standard in the literature. The data of interest consists of yearly observations of global mean temperature, measured in degrees Celsius above the 1951-80 average. The global mean is calculated via an equally weighted average of various land stations across the globe. The data is not without possible problems, although these are considered small (see Folland, Karl, and Vinnikov, 1990 for details).

We use the data set for GHG concentrations developed by Keeling, et. al. (1989). Carbon dioxide concentrations are in gigatons, and all other GHGs are converted to CO_2-equivalent concentrations and the data is also yearly. The data was constructed from a mix of ice core data until 1958 and then direct observation from Mauna Loa, Hawaii. The data set is also commonly used in the literature.[3]

Table (1) gives summary statistics of the data set, and Figure (1) and (2) plot the data. Both forcing and temperature trend upward.

V. Results

We first estimate equation (2c) as an experiment to see what is in the data. Table (2) gives the results. We see that the climate sensitivity is .29, indicating an equilibrium temperature change of 1.27 degrees Celsius. The standard error is low, 95 percent confidence bounds fall at 1.49 degrees C and 1.16 degrees C. Thus standard regression analysis implies that forcing from emission of CO_2 results in climate change with 95 percent confidence. The R^2 is .63, indicating that variation in forcing explains a majority of the variation in temperature. However, the results may be spuriously precise if both variables are non-stationary.

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[3] Since CO_2 mixes evenly in the atmosphere, there is no problem associated with collecting the data at only one site.

Hence we consider the hypothesis that there is a unit root in the temperature and/or forcing series. If we can reject a unit root, we can reject the hypothesis that the upward trend is due to climate intertia, adding significant strength to the above result.

There are several proposed tests for the possibility of a unit root. A classic test is the augmented Dickey-Fuller (ADF) test (Hamilton, 1994). The ADF test (in the most general form) consists of a regression of a variable on lagged values, a constant, and a time trend:

$$\Delta y_t = a_0 + \gamma y_{t-1} + a_2 t + \sum_{i=1}^{P-1} \beta_i \Delta y_{t-i} + u_t \qquad (5a)$$

subject to:

$$\beta_i = -\sum_{k=i+1}^{P} \gamma_i \qquad (5b)$$

Consider the hypothesis $\gamma = 0$. If true, then (5a) reduces to an AR process in the first differences, where it is easy to see that shocks do not die out regardless of β. The ADF test thus accounts for integrated processes that are fractional or are of order greater than one as well as a random walk. If we reject $\gamma = 0$, then we reject a unit root in the level of y_t. Critical values are adjusted for the autocorrelation present in the data. Table (3) gives the result of the ADF test along with critical values. From the results, we can see that we are unable to reject a unit root in the temperature series at even the 90 percent level. The results are consistent regardless of whether or not a time trend is included in the regression. Hence the temperature series is best described as a unit root as opposed to a time trend (a sensible result, since it is unlikely that the mean temperature is simply trending upward towards infinity). However, as seen in Table (3), we soundly reject a unit root in the first difference of temperature.

We also calculate the ADF test statistic for the forcing variable. Table (3) gives the results. When a time trend is not included, we cannot reject the presence of a unit root. However, when a time trend is included, a unit root is rejected. In fact, a quadratic time trend fits the forcing data nearly perfectly. The forcing variable comes from GHG emissions, which in turn comes from industrial production and energy consumption. One possible explanation is that the time trend results from improvements in technology, which generate additional production and/or consumption of energy. Another possibility is that increased energy usage comes from economic growth and capital formation. Neither points directly to a unit root versus a time trend in the forcing data. In any event, both the temperature and forcing variables are non-stationary, so there is a real problem that the relationship between temperature and forcing might be spuriously precise, which must be corrected for.

That unit root tests lack power is well-known (see Stock, 1995 for a survey). Thus, the above results do not show that there is in fact a unit root in temperature (i.e. that shocks to the climate persist forever), but merely that statistical inference from the data set is difficult because the climate may be subject to shocks which are long in duration relative to the size of the data set (which clearly fits with the idea that long run trends such as ice ages persist for much longer than the 140 year modern data set).

One possible cause of unit roots and spurious regressions is cointegration. Cointegration occurs when the dependent variable and the independent variable are subject to the same shocks. In the case of climate change, cointegration is unlikely for theoretical reasons. Shocks to temperature include such things as solar irradiation and volcanic eruptions, while shocks to GHG concentrations include technology shocks (inventions of new products or changes in tastes and preferences for goods such as autos which emit CO_2). Still, on some level cointegration is possible, for example warm weather could both increase temperature and result in increased travelling, which results in higher CO_2 emissions.

However, we do not find evidence of cointegration statistically. First, since we can reject a time trend but not a unit root in temperature and the reverse for forcing, the same shock process cannot drive both models. To be certain, we ran the Johansen cointegration test for temperature and forcing with and without the time trend. As shown in Table (4), we can reject the null hypothesis of no cointegration with 95% confidence if a time trend is not included. When a time trend is included, we cannot reject the hypothesis of no cointegration. Hence cointegration is not likely, as we might suspect on theoretical grounds.

One way to correct for the non-stationary variables in the regression is first differencing. First differencing in essence assumes that the dependent variable has a unit root. First differencing equation (2c) gives:

$$T_t - T_{t-1} = \alpha_1 (F_t - F_{t-1}) + u_t - u_{t-1} \tag{6a}$$

or:

$$T_t = T_{t-1} + \alpha_1 (F_t - F_{t-1}) + u_t - u_{t-1} \tag{6b}$$

We regress the first difference of temperature on the first difference of forcing. We summarize the results in Table (5). As predicted by the theory, the coefficient of the forcing term is relatively unchanged, now at .34. There is no concept of the equilibrium temperature change here because we assume a unit root, which implies that changes in GHG concentrations cause permanent changes in temperature. Hence a doubling of GHGs would eventually result in an undefined temperature.

Although the coefficient is relatively unchanged, the standard errors are significantly higher. In fact, the coefficient is no longer significantly different than zero, indicating that we cannot reject the hypothesis that there is no climate change from radiative forcing. Furthermore, the R^2 is almost zero, indicating that forcing has no power to explain variations in temperature. Hence, authors are justified in their concern about the possibility of long run cycles in the climate.

One possible problem with first differencing is that first differencing is not robust to the presence of a near unit root. That is, if the coefficient of lagged temperature is close to one, but not exactly equal to one, then first differencing results in misspecification error. Suppose the true coefficient of lagged temperature is $\beta_1 < 1$. Then temperature evolves according to equation (3b):

$$T_t = \beta_0 + \beta_1 T_{t-1} + \beta_2 F_t + \varepsilon_t$$

Adding and subtracting T_{t-1} gives:

$$T_t = T_{t-1} + \beta_2 (F_t - F_{t-1}) + [\beta_0 + (\beta_1 - 1) T_{t-1} + \beta_2 F_{t-1} + \varepsilon_t] \tag{7}$$

Hence three variables are included in the error term of equation (6b), resulting in misspecification. Here a near unit root is a strong possibility because otherwise we must believe shocks to the global mean temperature are permanent.

An alternative procedure is to use FM-OLS or equivalently ALS, which is robust to the presence of both a near unit root and a unit root in the temperature series. Given that ALS and FM-OLS are robust in this sense, they are more appropriate versus first differencing.

Accordingly, we estimated equation (8) using ALS. To describe ALS concisely, suppose we have a model:

$$Y_t = \beta' X_t + \varepsilon_t \tag{9}$$

Then the ALS estimator consists of running the regression:

$$Y_t = \alpha + \beta X_t + \sum_{j=-K_1}^{K_2} \phi_j \Delta X_{t-j} + u_t \tag{10}$$

The leads and lags included in the ALS regression act to remove the serial correlation in ε_t. An important decision is the number of leads and lags to include, K_1 and K_2, which are generally chosen so as to reduce the regression error to white noise. Application of ALS to our model requires some care. For example, we cannot include as a regressor the +1 lead value of the independent variable T_{t-1}, since this is the dependent variable. Furthermore, since F_t is very close to a time trend, all leads and lags of ΔF_t are near perfectly correlated with the constant term and each other. Hence we must omit leads and lags of ΔF_t as well as the first lead of ΔT_{t-1}.

We ran ALS for combinations of $K_1 = 1,2,3$ and $K_2 = 1,2,3$, excluding leads and lags of ΔF_t and the first lead of ΔT_{t-1}. The regression with the closest errors to white noise consisted of the +2 and –2 lags only. The results for this regression are summarized in Table (6). From Table (6), we see that the +2 lead of ΔT_{t-1} was significant. The overall equilibrium temperature change fell to 1.30, with a standard error of .173, which is almost double the original regression.

However, the 95% lower bound on the equilibrium temperature change is near one, indicating that the forcing effect remains even after correction for unit roots.

Finally, we also ran the regression with $K_1 = 0$ and $K_2 = 0$. This regression outperformed all others, the errors had even less serial correlation than the +2, -2 regression. This regression, given in Table (7), gives similar numbers for the equilibrium temperature change: 1.33 degrees Celsius with a standard error of .163. In fact, all combinations of K yield quite similar results for the standard error of the equilibrium temperature change from a doubling of GHGs.

The results of the robust analysis using ALS imply twice the uncertainty regarding the effect of anthroprogenic GHG emissions than might be surmised from a regression which implicitly assumes the change in temperature does not result from climate inertia alone. The above regression therefore quantifies the additional uncertainty due to the possibility that the observed warming is not due to GHG emissions, but instead reflects the slow propagation of climate shocks.

VI. Conclusions

There has been much concern over the possibility that the relationship between GHGs and global mean temperature is spuriously precise: that the primary cause of the modern era temperature rise is merely the inertia of the climate playing out over a time scale of many centuries. Our first result is that these concerns are well-founded. We could not reject a unit root in the temperature series (and we could not reject a time trend in the forcing series). Both series are non-stationary. When the regression was adjusted for the possibility of a unit root, the standard error of the equilibrium temperature change doubled. However even after accounting for these concerns the relationship is still strongly significant, with a 95% confidence lower bound of about 1 degree Celsius for a doubling of GHGs.

The results have strong policy significance. The results imply first that a GHG effect is a more robust result, strengthening the argument for control of GHGs. Second, we cannot reject a unit root in the climate. Hence, there is a possibility that shocks to the climate persist for a very long time. In this case, emission of GHGs now will warm the climate for years or even centuries, which would imply an irreversibility problem. Thus there may be a strong option value to controlling emissions now. Finally, further reductions in uncertainty about the climate sensitivity caused by the possibility of climate inertia are unlikely any time soon (because of the low power of the unit root test). The policy debate can be largely characterized by those who advocate a wait-and-see policy versus those who advocate acting now. The wait-and-see policy is inherently based on the value of improved decisions arising from reducing uncertainty. Our results indicate that waiting will produce little reduction of uncertainty.

An avenue for future research is to test for unit roots in longer data sets based on climate sensitive phenomena. However as noted earlier, these data sets are subject to more error and tend to show less climate change than the global mean temperature data.

VII. References

Bassett, Gilbert W. Jr., "Breaking Recent Global Temperature Records," *Climatic Change*, 21:303-315 (1992).

Cubasch, U. and Cess, R., "Processes and Modeling," Ch. 7 in J.T. Houghton et al. (eds.), *Climate Change: The IPCC Scientific Assessment* (Cambridge University Press, Cambridge, 1990).

Enders, Walter, *Applied Econometric Time Series* (Wiley, New York, 1995).

Folland, C., Karl, T., and Vinnikov, K., "Observed Climate Variations and Change," Ch. 7 in J.T. Houghton et al. (eds.), *Climate Change: The IPCC Scientific Assessment* (Cambridge University Press, Cambridge, 1990).

Granger, C. and Newbold, P., "Spurious Regressions in Econometrics," *Journal of Econometrics*, 2:111-20 (1974).

Hammer, C., "Past Volcanism Revealed by Greenland Ice Sheet Impurities," *Nature*, 270:482-486 (1977).

Hamilton, J., *Time Series Analysis* (Princeton University Press, Princeton, NJ, 1994).

Keeling, C., Bacastow, R., Carter, A., Poper, S., Whorf, T., Heimann, M., Mook, W., and Roeloffzen, H., "A Three Dimensional Model of Atmospheric CO_2 Transport Based on Observed Winds: 1. Analysis of Observational Data in: Aspects of Climate Variability the Pacific and the Western Americas," in Peterson, D. (ed.), *Geophysical Monograph* (AGU, Washington, 1989).

Kelly, D. and Kolstad, C., "Bayesian Learning, Pollution, and Growth," *Journal of Economic Dynamics and Control*, 23:491-518 (1999).

W.D. Nordhaus, *Managing the Global Commons: The Economics of Climate Change* (MIT Press, Cambridge, Mass., 1994).

Porter, S., "Pattern and Forcing of Northern Hemisphere Glacier Variations During the Last Millennium," *Quarterly Resources*, 26:27-48 (1986).

Schlesinger, M. and Andronova, N., "Observationally Determined Climate Sensitivity and Its Probability Distribution," Unpublished manuscript, University of Illinois (1996).

Schlesinger, M., Jiang, X., and Charlson, R., "Implication of Anthroprogenic Atmospheric Sulfate for the Sensitivity of the Climate System," in Rosen, L. and Glasser, R. (eds.), *Climate Change and Energy Policy: Proceedings of the International Conference on Global Climate Change: Its Mitigation Through Improved Production and Use of Energy* (Cambridge University Press, 1992).

Schlesinger, M. and Ramankutty, N., "Implications for Global Warming of Intercycle Solar-Irradiance Variations," *Nature*, 360:330-333 (1992).

Schlesinger, M. and Ramankutty, N., "Is the Recently Reported 65- to 70-Year Surface-Temperature Oscillation the Result of Noise?" *Journal of Geophysical Research*, 100:13767-13774 (1995).

Shine, K. P., Derwent, R. G., Wuebbles, D. J., and Morcrette, J-J., "Radiative Forcing of Climate," Ch. 2 in J.T. Houghton et al. (eds.), *Climate Change: The IPCC Scientific Assessment* (Cambridge University Press, Cambridge, 1990).

Stock, J., "Unit Roots, Structural Breaks, and Trends," in Engle, R. and McFadden, D. (eds.), *Handbook of Econometrics* (North Holland, 1995).

Vinnikov, K., Groisman, P., and Lugina, K., "Empirical Data on Contemporary Global Climate Changes (Temperature and Precipitation)," *Journal of Climate*, 3:662-677 (1990).

Wigley, T. and Barnett, T., "Detection of the Greenhouse Effect in the Observations," Ch. 8 in J.T. Houghton et al. (eds.), *Climate Change: The IPCC Scientific Assessment* (Cambridge University Press, Cambridge, 1990).

VIII. Appendix I: Figures

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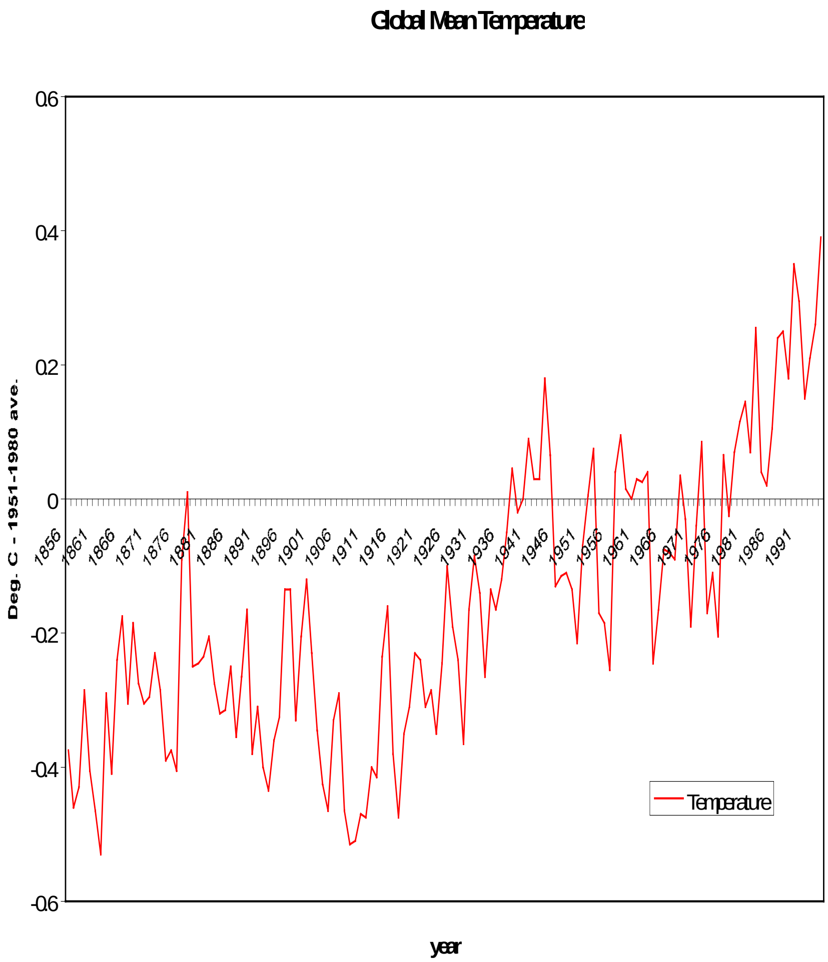

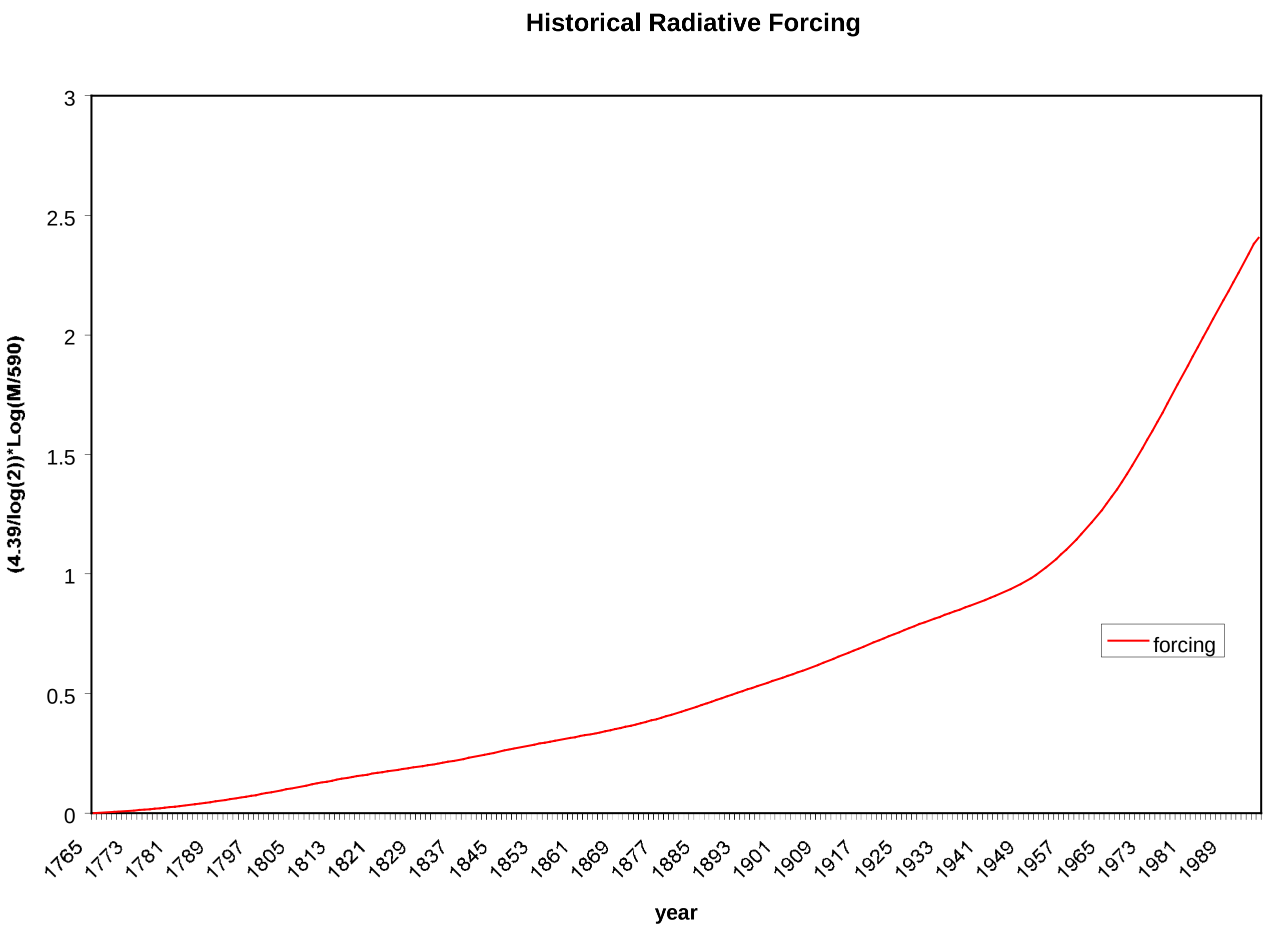
Historical Radiative Forcing
3
2.5
2
1.5
1
0.5
0
(4.39/log(2))*Log(M/590)
forcing
1765
1773
1781
1789
1797
1805
1813
1821
1829
1837
1845
1853
1861
1869
1877
1885
1893
1901
1909
1917
1925
1933
1941
1949
1957
1965
1973
1981
1989
year

IX. Appendix II: Tables

Series	Temp (T_t)	Forcing (F_t)
Mean	-0.163357	0.612523
Median	-0.187500	0.417300
Maximum	0.3900000	2.405800
Minimum	-0.530000	0.000000
Std. Dev.	0.205011	.588349
Skewness	0.435273	1.299411
Kurtosis	2.534017	4.004107
Jarque-Bera	5.687442	4.71023
Probability	0.058209	0.00000
Sample: 1861-1995 (140 observations)		

Table 1: Descriptive Statistics

Variable	Coefficient	Std. Error	t-Statistic
Constant	-0.431553**	0.020397	-21.15722
F_t	0.289657**	0.018847	15.36854
Implied T_{2x}	1.27**	0.082738	16.07484
R-squared	0.631205	Mean dependent var	-0.163357
Adjusted R-squared	0.628533	S.D. dependent var	0.205011
S.E. of regression	0.124951	Akaike info criterion	-4.145492
Sum squared resid	2.154544	Schwarz criterion	-4.103469
Log likelihood	93.53305	F-statistic	236.1919
Durbin-Watson stat	0.838716	Prob(F-statistic)	0.000000

Table 2 : OLS regression (**: significant at the 1% level).

Variable	ADF Test Statistic	MacKinnon Critical Values		
		1%	5%	10%
T_t	-2.447045	-4.0283	-3.4435	-3.1462
ΔT_t	-7.602243**	-4.0288	-3.4437	-3.1464
F_t, time trend	-5.533682**	-4.0017	-3.4308	-3.1387
F_t, no time trend	-1.445	-4.0017	-3.4308	-3.1387

Table 3: Unit root tests (**: reject unit root at the 1% level).

Variable	ADF Test Statistic for null of no cointegration	MacKinnon Critical Values	
		99%	95%
T_t and F_t, no time trend	-3.096024*	-3.4796	-2.8828
T_t and F_t, time trend	-3.084263	-4.0283	-3.4435

Table 4: Unit root tests, cointegration (*: reject at the 5% level).

Variable	Coefficient	Std. Error	t-Statistic
ΔF_t	0.345414	0.494402	0.698650
Implied T_{2x}	N/A	N/A	N/A
R-squared	0.001205	Mean dependent var	0.005504
Adjusted R-squared	0.001205	S.D. dependent var	0.114495
S.E. of regression	0.114426	Akaike info criterion	-4.328482
Sum squared resid	1.806884	Schwarz criterion	-4.307370
Log likelihood	104.5970		
Durbin-Watson stat	2.373708		

Table 5: OLS regression, data first differenced.

Variable	Coefficient	Std. Error	t-Statistic
Constant	-.172779**	0.034036	-5.076097
F_t	0.12058**	0.024918	4.839115
T_{t-1}	0.593331**	0.070018	8.473936
ΔT_{t-2}	-0.115148	0.077074	-1.493988
ΔT_{t+2}	-0.265447**	0.074260	-3.574543
Implied T_{2x}	1.30166**	0.173372	7.507915
R-squared	0.757932	Mean dependent var	-0.164852
Adjusted R-squared	0.750484	S.D. dependent var	0.195090
S.E. of regression	0.097950	Akaike info criterion	-4.610258
Sum squared resid	1.247252	Schwarz criterion	-4.502655
Log likelihood	124.6357	F-statistic	101.7601
Durbin-Watson stat	2.379805	Prob(F-statistic)	0.000000

Table 6: Augmented Least Squares, most uncorrelated residuals: $K_1 = 2$, $K_2 = 2$.

(**: significant at the 1% level).

Variable	Coefficient	Std. Error	t-Statistic
Constant	-0.182831**	0.034276	-5.334117
F_t	0.127121**	0.024925	5.100201
T_{t-1}	0.581317**	0.069930	8.312807
Implied T_{2x}	1.333**	0.163620	8.146926
R-squared	0.753667	Mean dependent var	-0.161835
Adjusted R-squared	0.750045	S.D. dependent var	0.204957
S.E. of regression	0.102469	Akaike info criterion	-4.535039
Sum squared resid	1.427992	Schwarz criterion	-4.471705
Log likelihood	120.9528	F-statistic	208.0495
Durbin-Watson stat	1.967868	Prob(F-statistic)	0.000000

Table 7: OLS regression, equivalent to Augmented Least Squares: $K_1 = 0, K_2 = 0$. (**: significant at the 1% level).

OTHER TABLES

1. CORRELATION STRUCTURE

	TEMP	TEMP(-1)	FORCING	FORCING(-1)
TEMP	1.000000	0.840567	0.792782	0.793971
TEMP(-1)	0.840567	1.000000	0.782300	0.783346
FORCING	0.792782	0.782300	1.000000	0.999971
FORCING(-1)	0.793971	0.783346	0.999971	1.000000

2. ADF OUTPUT, TEMPERATURE

Variable	Coefficient	Std. Error	t-Statistic
TEMP(-1)	-0.222227	0.090814	-2.447045
D(TEMP(-1))	-0.183639	0.109955	-1.670138
D(TEMP(-2))	-0.265700	0.103839	-2.558771
D(TEMP(-3))	-0.193760	0.095547	-2.027897
D(TEMP(-4))	-0.049785	0.089636	-0.555416
C	-0.097456	0.043780	-2.226035
@TREND(1856)	0.000982	0.000406	2.419352
R-squared	0.222634	Mean dependent var	0.005889
Adjusted R-squared	0.186195	S.D. dependent var	0.114769
S.E. of regression	0.103535	Akaike info criterion	-4.485239
Sum squared resid	1.372085	Schwarz criterion	-4.334595
Log likelihood	118.1970	F-statistic	6.109754
Durbin-Watson stat	1.993081	Prob(F-statistic)	0.000012

2. ADF OUTPUT, CHANGE IN TEMPERATURE

Variable	Coefficient	Std. Error	t-Statistic
D(TEMP(-1))	-2.381088	0.313209	-7.602243
D(TEMP(-1),2)	1.015976	0.269352	3.771925
D(TEMP(-2),2)	0.588635	0.212505	2.769981
D(TEMP(-3),2)	0.259368	0.149019	1.740509
D(TEMP(-4),2)	0.107377	0.088489	1.213452
C	0.000642	0.019393	0.033111
@TREND(1856)	0.000165	0.000237	0.698203
R-squared	0.661483	Mean dependent var	0.001418
Adjusted R-squared	0.645490	S.D. dependent var	0.177450
S.E. of regression	0.105655	Akaike info criterion	-4.444326
Sum squared resid	1.417701	Schwarz criterion	-4.292946
Log likelihood	114.6321	F-statistic	41.36103
Durbin-Watson stat	1.999414	Prob(F-statistic)	0.000000

3. ADF OUTPUT, FORCING + TIME TREND

Variable	Coefficient	Std. Error	t-Statistic
FORCING(-1)	-0.004872	0.000880	-5.533682
D(FORCING(-1))	1.696275	0.253844	6.682338
D(FORCING(-2))	-0.417261	0.463610	-0.900026
D(FORCING(-3))	-1.131782	0.463374	-2.442480
D(FORCING(-4))	0.992166	0.265811	3.732601
C	-0.000826	0.000218	-3.784863
@TREND(1765)	2.14E-05	3.93E-06	5.444199
R-squared	0.990937	Mean dependent var	0.010626
Adjusted R-squared	0.990688	S.D. dependent var	0.011377
S.E. of regression	0.001098	Akaike info criterion	-13.59824
Sum squared resid	0.000264	Schwarz criterion	-13.49230
Log likelihood	1222.921	F-statistic	3990.653

Durbin-Watson stat	1.366268	Prob(F-statistic)	0.000000

4. GRANGER CAUSALITY TESTS (**: significant at the 1% level).

Null Hypothesis:	Obs.	F-Statistic	Probability
FORCING does not Granger Cause TEMP	136	3.71846**	0.00676
TEMP does not Granger Cause FORCING	136	0.53287	0.71180