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Causality from long-lived radiative forcings to the climate trend

Francisco Estrada[1,2] and Pierre Perron[3]

[1]Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Mexico City, Mexico. [2]Institute for Environmental Studies, VU University Amsterdam, Amsterdam, the Netherlands. [3]Department of Economics, Boston University, Boston, Massachusetts

Address for correspondence: Francisco Estrada, Centro de Ciencias de la Atmósfera, Universidad Nacional Autónoma de México, Ciudad Universitaria, Circuito Exterior, 04510 Mexico City, Mexico. feporrua@atmosfera.unam.mx

In our study, we present a purely statistical observations-based model-free analysis that provides evidence about Granger causality (GC) from long-lived radiative forcings (LLRFs) to the climate trend (CT). This relies on having locally ordered breaks in the slopes of the trend functions of LLRF and the CT, with the break for LLRF occurring before that of the CT and with the slope changes being of the same sign. The empirical evidence indicates that these conditions are satisfied empirically using standard global surface temperature series and an aggregate measure of LLRF (carbon dioxide, nitrous oxide, and chlorofluorocarbons). We also discuss why the presence of broken trends can lead one to conclude in favor of GC when using standard methods even if the noise function in LLRF is negligible.

Keywords: climate change; attribution; causality; econometric methods; time series

Introduction

The attribution of climate change to human activities has been discussed at length in the literature and, regardless of the differences in assumptions and methods, there is a consensus about the existence of a common secular trend between temperatures and radiative forcing variables. The contributions of Working Groups I and II of the Intergovernmental Panel on Climate Change provide direct and indirect scientific evidence about the warming of the climate system and of the role of anthropogenic activities.[1,2] Comparing observations to model predictions about what the state of a variety of systems would be with or without anthropogenic forcings has greatly increased the confidence about a strong influence of human activities on the observed climate. Of importance, to conduct attribution studies is the optimal fingerprinting method[3,4] based on a generalized multivariate regression for the detection and attribution of changes to externally forced climate change signals.[1] These optimal detection analyses that combine observed and modeled climate data provided important evidence to support IPCC's verdict that "most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas concentrations."[1,5,6] Nonetheless, it has been argued that attribution studies based on climate models' simulations can be criticized of circular reasoning.[7] One important contribution of statistical attribution methods is that they can provide evidence that does not depend on the physical climate models' performance for reproducing the observed climate.

However, taking the stand of a climate skeptic or a climate denier, some of this evidence may be viewed as falling short of being convincing. First, as is so often said in various blogs and other outlets, correlation does not imply causation. This is indeed correct and points to the fact that establishing a similar trend for radiative forcings and temperatures is no indication of causation. In fact, if radiative forcings had any linear trend behavior, the correlation coefficient with temperatures would be nearly one; a standard

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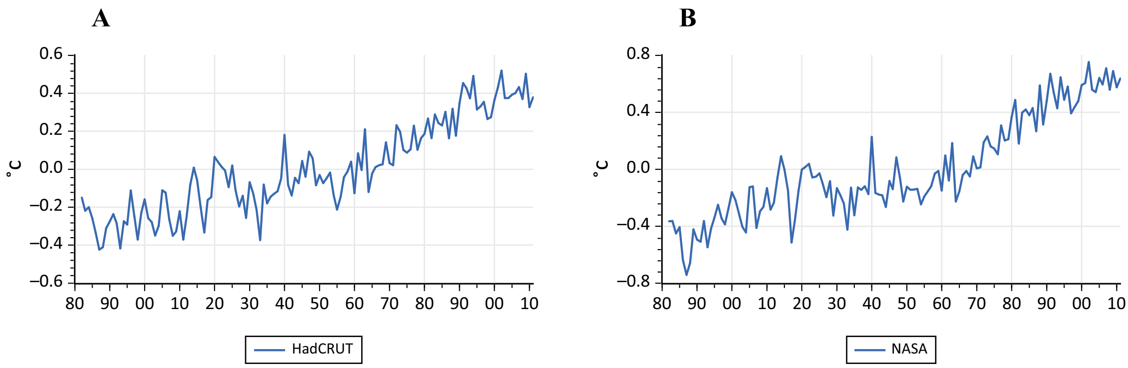

Figure 1. Filtered global temperatures. Panels (A) and (B) show global temperatures for the HadCRUT4 and the NASA data sets, respectively.

pitfall in dealing with trending series. Second, the various calibrated models used could be criticized as being imprecise and providing widely different forecasts or simulations.[8–11] They could also be tweaked to generate the desired results. Hence, the causality claim obtained from such model-based studies may be questioned. We do not ascribe to this view but for the sake of arguments, highlight that this is a view often put forward by climate skeptics.

The issue is then as follows. Is it possible to provide a purely statistical observations-based model-free analysis that provides evidence about causality from long-lived radiative forcings (LLRFs) to the climate trend (CT)? Our answer is yes provided there are locally ordered breaks in the slopes of the trend functions of LLRF and the CT, with the break for LLRF occurring before that for the CT and with the slope changes being of the same sign. What we label as the CT should be viewed as an estimate of the underlying trend in temperatures, that is, long-run secular movements not due to natural variability.

The LLRF are defined as components having a long atmospheric residence time, namely carbon dioxide (CO_2), nitrous oxide (N_2O), and chlorofluorocarbons (CFCs), which have a so-called lifetime in excess of 45 years, defined as the period it takes for a perturbation to be reduced to 37% of its initial amount. Given the time span of the historical records under study, we can for all practical purposes view the effect of such deviations as having a permanent effect. We focus on LLRF for the following reasons. First, these are the most contentious components in the debate about the attribution of climate change, especially CO_2. It is well agreed that nonanthropogenic factors, such as solar irradiance variations and volcanic eruptions have a short-term impact on surface temperatures and barely none on the CT. Some anthropogenic factors may have a short-term effect on temperatures and the CT but, given the short-term nature of their effect, they could be considered of second order. This does not mean they are not important or to be ignored but simply that their long-term effect on climate is dwarfed by those of the LLRF.

We shall use the concept of Granger causality (GC).[12] Briefly, if one considers a bivariate system consisting of LLRF and the CT, then LLRF causes CT if one can better predict CT using the past of LLRF and CT than what can be done using only the past of CT. This is a purely statistical concept of causality and most often assessed using linear predictors. It has been applied in various studies to show causality from various sets of anthropogenic factors to CT using standard procedures suggested in the econometrics literature; see below for details and references. Our argument is that such a causality argument can be made in a simpler way and that our suggested approach is encompassing in that it also explains some of the prior results. As discussed, GC from LLRF to CT holds when the trend function of both series have locally ordered breaks with the break in the slope occurring first in LLRF and with the slope changes being of the same sign. This is because at some part of the sample, say postbreak, it is possible to better forecast CT using the past (say between the breaks in LLRF and CT) of LLRF and CT over and above what can be achieved using the same past values of CT. The intuition is quite straightforward. Suppose two individuals walk along a street one ahead of the other (i.e., common linear trend). Then, even though their paths are common, it is very difficult to argue that the first (think of LLRF) causes the travel path of the second (CT). They may simply walk along the same street by chance. However, suppose you suddenly witness the first one (LLRF), taking a quick right turn with increasing speed (faster rate of growth), with the second one (CT) subsequently also taking the same right turn at increasing speed and thereby going in the same different direction. In this case, one would be quite convinced that the second individual is purposefully following the first and that the actions of the first cause those of the second. This is why breaks in the trend function can be used to identify causality properties. It is deceptively simple, yet quite compelling.

The paper is structured as follows. First, it presents the data used, the transformation considered and the sources. Second, it provides a brief review of some time series concepts used in our analysis. A statistical analysis of the trend in LLRF is presented next. Then, it provides empirical evidence supporting the fact that LLRF Granger causes temperatures. There, we discuss of the implications of the results for conducting standard GC tests. Finally, it provides brief concluding remarks.

Data

The global surface temperature data used in this paper come from the Climatic Research Unit's HadCRUT4[13] and the NASA database.[14,15] These databases differ basically in two aspects: (1) how regions without observing stations are accounted for (e.g., extrapolation methods). The HadCRUT4 excludes most of the Arctic, where the warming has been very large during the past decade; and (2) how sea surface temperatures are adjusted due to changes in measurement methods. To represent the most important natural sources of interannual global and hemispheric climate variability, we use the following indices,[16–18] the Atlantic Multidecadal Oscillation (AMO) and the North Atlantic Oscillation (NAO). These series are used to filter out the effects of natural variability oscillations on global temperatures series. The radiative forcing series cover the period of 1880–2011 and are available from the NASA Goddard Institute for Space Studies.[19] They represent the effective radiative forcing that includes a number of rapid adjustments to the radiative imbalance.[20] We use the LLRF (CO_2, N_2O, and CFCs), the WMGHG (LLRF plus methane (CH_4)), and the total radiative forcing (TRF), which includes WMGHG plus ozone (O_3), stratospheric water vapor (H_2O), solar irradiance, land use change, snow albedo, black carbon, reflective tropospheric aerosols and the indirect effect of aerosols. The data are available from: http://www.metoffice.gov.uk/hadobs/hadcrut4/; http://data.giss.nasa.gov/gistemp; ftp://ftp.ncdc.noaa.gov/pub/data/scpub201506/; http://www.esrl.noaa.gov/psd/data/timeseries/AMO/; http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nao.long.data; http://data.giss.nasa.gov/modelforce/Fe_H11_1880-2011.txt.

As in other recent studies,[8,21] we use a filtered version of the temperature series. Since trends and breaks are low-frequency features, it is important to purge the temperature series from natural low-frequency components. This allows more precise estimates of the break dates. Other high-frequency fluctuations in temperature series do not affect the precision of the estimates of the break dates and the magnitudes of the changes in slope. Here, we shall follow Ref. 21 and use the series filtered from the effect of the AMO and NAO; that is, we use the residuals from a regression of CT on AMO and NAO. The choice of AMO and NAO is dictated by their low-frequency effect on global temperatures.[22–24] Other natural variability modes may have an important effect on temperatures, although previous results suggest that they do not bias the issue of identifying trends and breaks. The two filtered temperature series are presented in Figure 1. The LLRF, WMGHG, and TRF series are presented in Figure 2. All series show a marked increase in the rate of growth around 1960. This will be central to our analysis. The temperature series also show a marked decrease in the mid-1990s, the so-called *hiatus.* This decrease is present though mild in the LLRF series; there was an important decrease in CFCs but somewhat compensated by an increase in the rate of growth of CO_2. One can see a more pronounced decrease in the rate of growth around this time in WMGHG because of the decrease in the emission of CH_4 and an even more pronounced decrease in the rate of growth in TRF, mostly because of the decrease

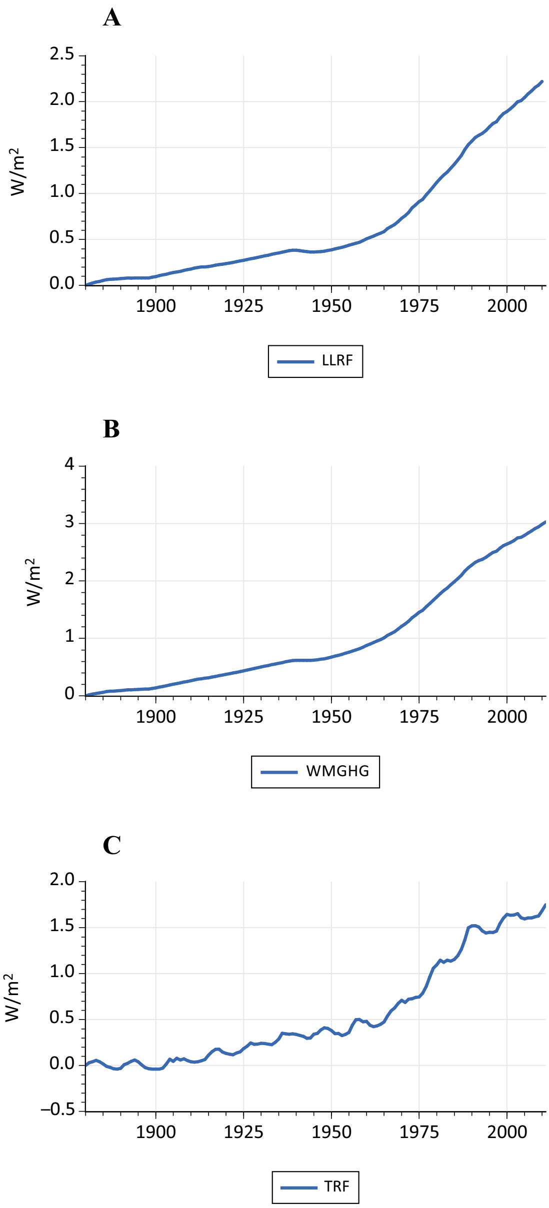

Figure 2. Radiative forcing series. Panel (A) shows the long-lived radiative forcing (LLRF). Panel (B) shows the radiative forcing of the well-mixed greenhouse gases (WMGHG). Panel (C) shows the total radiative forcing (TRF).

in the indirect effect of aerosols (see Ref. 8 and the references therein). This suggests that, while the hiatus was indeed caused by anthropogenic radiative factors, much of the effect is likely to be transient given that it is mostly due to non-LLRF factors. Since our focus is about the effect of LLRF on the CT, we do not consider the break related to the hiatus but focus on the break in the 1960s. This is done without the loss of generality for the arguments proposed.

Brief review of time series concepts

We briefly review concepts related to time series processes, in particular the difference between trend stationary (TS) and unit root (UR) processes. See Ref. 11 for a more detailed review with a focus on climate change issues. Consider a time series y_t with the following decomposition: $y_t = \tau_t + z_t$, where τ_t is the deterministic trend function and z_t is the noise component. A process is said to be integrated of order d or $I(d)$ if the dth difference of the noise z_t, $\Delta^d z_t = (1 - L)^d z_t$, is stationary. If a time series is stationary around an appropriately defined trend τ_t, its order of integration is 0 or $I(0)$. The process is said to be $I(1)$ if the deviations from the trend have to be differenced once to achieve stationarity. Consider the first-order autoregressive model

$$z_t = \alpha z_{t-1} + e_t, \quad e_t \sim \text{i.i.d.}\left(0, \sigma^2\right). \quad (1)$$

An example of a UR process is when $\alpha = 1$. Then, $\Delta z_t = z_t - z_{t-1} = e_t$. The first difference of the process is i.i.d. This model has the following implications. First, each shock e_t has a long-term effect on the level of z_t. To see this, write (1) with $\alpha = 1$ as (by recursive substitution) $z_t = z_0 + \sum_{j=1}^{t} e_j$. Since each shock has a permanent effect on future levels of z_t, a 1% unexpected increase in z_t today increases our predicted value of future z_t's by 1% for all future periods. In this simple example, with $e_t \sim$ i.i.d., z_t is called a random walk, the best predictor of z_t tomorrow being z_t today. Assuming this type of process as a representation of global and hemispheric temperatures implies that the secular movement of the series is determined by the sum of random shocks: all shocks have permanent effects on temperature series and even shocks in the distant past are as important as present variations to determine the current value. The long-term forecast is always influenced by historical events, and temperature predictability is limited, even if forcing factors are held constant.[8,25,26] The second implication is that the variance of z_t increases with t since $\text{Var}(z_t) = \text{Var}(\sum_{j=1}^{t} e_j) = t\sigma^2$ if z_0 is fixed. This is a nonstationary process since its second moment depends on t. Hence, a UR process is nonstationary in variance. The process can cross any line within a long enough period. The random walk model is quite restrictive. Most of the time, allowing for additional short-run correlation is needed; that is, having $\Delta z_t = v_t$, where v_t is a stationary process exhibiting some correlation (without a UR itself). In this more general model, the same qualitative features hold with minor modifications.

A wide variety of time series have a tendency to show secular movements over time. Hence, it is common to specify the trend function as $\tau_t = \mu + \beta t$. Here, β is the slope of the trend, sometimes called the drift. Then, $\Delta y_t = \beta + v_t$ and $y_t = \mu + \beta t + \sum_{j=1}^{t} v_j$. The trend function of y_t is then composed of two parts: (i) a deterministic part given by the drift term and (ii) a stochastic part given by the permanent effect of each shock v_t on the level of y_t. Since shocks have a permanent effect, they change our long-term forecast of the level of the series. Such models are often labeled as difference stationary (DS) models.

When a set of series are integrated, this raises the possibility that they be cointegrated.[27] Suppose x_t and y_t are integrated of order one, then they are cointegrated if there exists some θ such that $x_t - \theta y_t$ is stationary. In this case, even though none of the variables is individually attracted to some trend function, the cointegrating relationship acts as an attractor between the two series. Also, cointegration implies that an error-correction model exists. The application of integrated and cointegrated concepts to address the issue of the attribution of climate change include Refs. 28–31 among many others. The use of this approach has also been criticized in the literature.[10,25,32]

An alternative to model variables that increase over time is with a purely deterministic trend, that is, $y_t = c + \beta t + w_t$, where w_t is a stationary process. This is called a TS model because the deviations from the trend function are transitory, that is, the shocks w_t have no permanent long-run effects. Distinguishing between a TS and DS process is the so-called UR testing problem.

A particular case of the TS process that has been discussed in the climate change literature is when breaks in the trend function are present. In general, the trend parameters and their structural changes need not to be assumed deterministic.[33–35] In order to illustrate the class of models that applies in such cases, suppose that:

$$y_t = \mu_t + \beta_t t + z_t,$$

where $\mu_t = \mu_{t-1} + v_t$ and $\beta_t = \beta_{t-1} + u_t$. The intercept and slope of the trend function can be time varying stochastic processes as in Ref. 34. However, when only one (or very few) break occurs, it becomes difficult to model the change with a stochastic structure. Hence, the common approach in the literature has been to consider the change as being exogenous in the sense of intervention analysis[36] and they are not explicitly modeled via a parametric stochastic structure. Under this parameterization, there are only some shocks that can change the long-term behavior of the time series, as opposed to a UR process for which all shocks have long-term effects. In the climate context, long-term changes are not frequent in the scale of the sample under analysis and are produced by important changes in key external forcing factors.[8,25] The application of TS models with changes in slopes to address the issue of attribution of climate change was used in Refs. 8–11,25,37, and 38, among others.

Testing for GC

If both LLRF and CT are TS, to test for GC one can simply use the following regression estimated by ordinary least squares (OLS), where a subscript "*" indicates a detrended variable:

$$\mathrm{CT}_t^* = \sum_{i=1}^{k} \alpha_i \mathrm{CT}_{t-i}^* + \sum_{i=1}^{k} \beta_i \mathrm{LLRF}_{t-i}^* + u_t \tag{2}$$

and test the joint null hypothesis $H_0 : \beta_1 = \cdots = \beta_k = 0$ using a standard F-test. In general, one can use the following regression whether the series are stationary or integrated:

$$\mathrm{CT}_t = c + \sum_{i=1}^{k} \delta_i \mathrm{CT}_{t-i} + \sum_{i=1}^{k} \phi_i \mathrm{LLRF}_{t-i} + u_t, \tag{3}$$

where $k = p + d$, p is the order of the autoregressive process, and d is the maximal order of integration in CT and LLRF, see Ref. 39. This approach has been used by Refs. 40 and 41; see Ref. 42 for a review.

The question being asked using specification (2) is then: do the past deviations from trend in LLRF_t help explain the deviation from trend in CT_t over and above what the past deviations from trend in CT_t can do? For specification (3), the interpretation is similar with the changes in levels instead of the deviations. Note that in both cases, additional regressors can be added in (2) and (3) to allow for exogenous factors; for example, solar irradiance or volcanos, or to account for other factors that may be responsible for the changes in CT. We shall not consider such extended systems as our interest is solely with respect to the effect of LLRF on CT with respect to issues related to trends and breaks. While it can be argued that solar irradiance has been trending, the trend has flattened when temperatures started to increase at a fast pace (around 1960) so that no evidence of GC can be found (see Refs. 43 and 44). From the available literature and basic climate change science, it is highly unlikely that omitted variables would cause a bias or a finding of spurious causality. Note also that one could follow an out-of-sample (predictive) GC analysis as in some of the references mentioned above. Considering such extensions would not add substance to our arguments, hence they will not be further discussed.

A statistical analysis of the trend in LLRF

The nature of the trend in the aggregated measure of radiative forcing can be thought of using the following decomposition of the time series properties of the ith forcing y_{it},

$$y_{it} = f_{it} + u_{it},$$

where f_{it} is the trend and u_{it} are deviations from the trend. The trend is of general form (including the nonlinear case) and intends to capture the sustained increase in the forcing; u_{it} represents the noise component. Shocks to short-lived radiative forcings (e.g., aerosols or solar irradiance) will dissipate shortly; while in the case of long-lived forcing the effect of shocks will be long lasting. The overall trend of the aggregate forcing is the sum of the individual trends of each forcing in the set. The same applies to the noise components. Since CO_2 is by far the most important forcing, the overall trend will be substantially influenced by the trend in CO_2.

The matter of interest related to whether the overall series are TS or integrated (i.e., having an autoregressive UR) refers to the nature of the deviations from trend for the components having a long atmospheric residence time, namely CO_2, N_2O, and CFCs. Given the time span of the historical records under study, for all practical purposes we can view the effects of such deviations as permanent. This

Table 1. Tests for the existence of a break in the slope of temperature and radiative forcing series, sample 1880–1986

Series		Series	
HadCRUT^F	1.83**	LLRF	3.30***
	(1963)	(second break)	(1992)
	[1948–1978]		[1989–1995]
NASA^F	3.38***	WMGHG	31.61***
	(1965)		(1961)
	[1953–1977]		[1960–1962]
LLRF	215.85***	TRF	74.43***
(first break)	(1963)		(1964)
	[1962–1964]		[1958–1970]

NOTE: The main entries are the values of the Perron and Yabu test.[48] *** and ** denote statistical significance at the 1% and 5% levels, respectively. The superscript F denotes filtered temperature series. The estimated break dates are given in parenthesis and their corresponding 95% confidence intervals are shown in brackets. The long-run variance is calculated using the Bartlett kernel and Andrews[54] automatic bandwidth selection method. For the second break in LLRF, the sample used is 1968–2010.

would lead to each of the long-lived forcings as having a UR representation and hence the aggregated forcing would be integrated of order one.

The central issue then is the nature of the deviations for the long-lived components. We estimated by OLS the break date for a joint-segmented trend model given by

$$\mathrm{LLRF}_t = \alpha + \beta t + \delta 1(t > T_B)(t - T_B) + u_t,$$

where $1(A)$ is the indicator function of the event A, T_B is the break date and u_t is a residual term. This was done for the periods of 1880–1986, and 1968–2010. The choice of the subsamples was dictated by a preliminary analysis of the dates of the breaks points; minor variations lead to similar results. The reason for applying the tests to different subsamples is because the estimate of a single break need not be consistent when two breaks are present[45] contrary to the case with stationary variables in which case each break dates can be estimated sequentially.[46,47] For each subsample, the Perron and Yabu test[48] rejected the null hypothesis of no break in favor of one break. Table 1 presents the estimates of the break dates and their confidence intervals for the period of 1880–1986 for LLRF, WMGHG, TRF, and CT (filtered HadCRUT and NASA). For LLRF, we consider two subsamples: 1880–1986 and 1968–2010. The point estimates are 1963 (95% CI: 1962–1964) and 1992

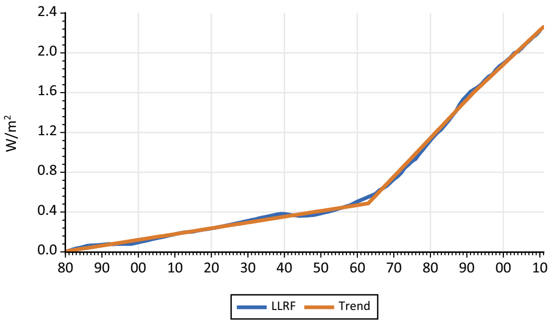

Figure 3. Long-lived radiative forcing (LLRF) and its deterministic trend with two breaks in slope in 1963 and 1992.

(95% CI: 1989–1995), where here and throughout, 95% CI indicates the 95% confidence interval constructed using the method of Perron and Zhu.[49] Figure 3 plots the fitted broken trend along with the original series. The distinctive feature is that the series is very smooth and follows the trend function very closely. Besides other minor nonlinearities, this is true except for one episode, namely the slowdown in LLRF during the period of 1940, driven by unprecedented reductions in CO_2 emissions most likely linked to the Great Crash and World War II. This slowdown can be viewed as a shock (a deviation from trend), though it occurred over several years and, hence, imparted an inflection point in the trend of LLRF instead of a sudden level shift. It nevertheless had a permanent effect in lowering the level of the aggregate radiative forcing (see Ref. 8, Section S6). Nevertheless, overall the deviations are essentially negligible. While this variable increased by 2.22 W/m^2 during the period 1880–2010, the estimates of the variance of the deviations from the fitted broken trend for LLRF is indeed close to 0 (0.0009). The coefficient of variation of LLRF is only 1%. In contrast, the variance of the deviations from the fitted trend for TRF is 0.0063, about an order of magnitude larger than that of LLRF. Global temperatures show much larger variability around their fitted trends with coefficients of variation of 13 and 18% for NASA and HadCRUT4, respectively (Table 2).

The crucial matter of interest is that the shocks or deviations from trend in the 1940s were the only nonnegligible ones that occurred in the sample; no important deviations from trend occurred in LLRF at any other time. In terms of the statistical model, the shocks to concentrations for those long-

Table 2. Increases in observed values, variances of deviations from trend, and coefficients of variation for LLRF, TRF, NASA^F, and HadCRUT^F

Series	Increase	Variance	Coefficient of variation
LLRF	2.22 (W/m^2)	0.0006	0.01
TRF	1.75 (W/m^2)	0.0063	0.05
HadCRUT^F	0.53 (°C)	0.0090	0.18
NASA^F	1.00 (°C)	0.0168	0.13

lived components have been around 0 throughout the sample, except for the slowdown in the 1940s. Hence, from a statistical point of view, it is more adequate to view the process describing LLRF as being a pure trend with an inflection point in the mid-20th century, a marked increase in slope in 1963 and a mild decrease in slope in 1992. When adding all other forcing factors with a short lifetime, for which deviations from trends with a transitory effect have occurred, this leads to a segmented trend model with stationary deviations (no UR) for more inclusive measures of TRFs that includes short-lived anthropogenic and natural factors (see TRF in Fig. 2).

Some authors have argued that because of the presence of LLRF, aggregate radiative forcings and, hence, temperatures must be integrated processes.[50,51] Their argument misses the distinction between the trend and the stochastic nature of the deviations from it. Suppose indeed that we have a UR process of the form

$$\mathrm{LLRF}_t = \mathrm{LLRF}_{t-1} + C_t,$$

where C_t is the yearly value of the addition to LLRF_t and can be specified has having some distribution with mean μ_t, say, and variance σ_C^2. This indeed does trivially define a UR process provided $\sigma_C^2 > 0$. Here, the issue is that $\sigma_C^2 \approx 0$ so that LLRF_t is the accumulation of the possibly time varying means μ_t. If μt is constant at some value μ, then $\mathrm{LLRF}_t = \mathrm{LLRF}_0 + \mu t$, a deterministic trend. The data show that μt is not constant throughout the whole sample period, but changes only rarely: (1) it increases in value in 1963, (2) decreases near 1992, and (3) shows some mild nonlinearities in the 1940s. Apart from that, it is otherwise constant.

Going back to the main features of UR processes described above, salient features are (1) all shocks have a permanent impact on the level of the series and (2) deviations from trend exhibit increasing variance through time. None of these features are present in LLRF. Only a brief spell around 1940 had a permanent impact and the deviations from trend are basically 0. Hence, essentially, it is better to view LLRF as a nonlinear trend with basically no randomness around it. When adding short-lived anthropogenic and natural factors, the total aggregate radiative forcing (TRF) is better described as a (nonlinear) TS process.

Causality with breaks in trend

In a bivariate system consisting of LLRF and CT, LLRF Granger-causes CT if one can better predict CT using the past of LLRF and CT than what one can do using only the past of CT. Suppose that

$$\mathrm{LLRF_t} = c_1 + \beta_1 t + \delta_1 1(t > T_{B1})(t - T_{B1}) + u_{1t},$$

$$\mathrm{CT_t} = c_2 + \beta_2 t + \delta_2 1(t > T_{B2})(t - T_{B2}) + u_{2t},$$

where u_{1t} and u_{2t} are, purely for simplicity, i.i.d. random processes. Note that for LLRF_t, u_{1t} is essentially 0 as discussed above. Since we shall consider forecasting CT_t using LLRF_t, the assumptions on u_{1t} and u_{2t} are innocuous. For the sake of exposition, suppose that $T_{B2} = T_{B1} + 1$ and we wish to forecast CT_t at time $T_{B2} + 1$. If one uses only the past values of CT_t, the forecast is then $c_2 + \beta_2(T_{B2} + 1)$ and the forecast error is $\delta_2 + u_{2t}$. On the other hand, if one uses both CT_t and LLRF_t, provided the slope changes are of the same sign, there is a linear combination of CT_{t-1} and LLRF_{t-1} such that the forecast is $c_2 + \beta_2(T_{B2} + 1) + \delta_2$ and the forecast error is u_{2t}. Hence, the forecast error is clearly reduced (either in mean or mean-squared error terms) when using the past of LLRF compared to what can be achieved using the past of CT only. This defines Ganger causality from LLRF to CT.

Empirical evidence

To establish GC from LLRF to CT, we must therefore verify the following features in the data: (1) the existence of a break in both LLRF and the temperatures series (filtered to adjust for the effect of AMO and NAO, as stated above), (2) the break date in LLRF occurs prior to that in temperatures, and (3) the pre- and postbreak slopes are of the same sign. To obtain point estimates, one does not need to take a stand on the nature of the noise components, that is, $I(0)$ or $I(1)$. In both cases, the estimate of the break fraction is consistent, though the break dates themselves are consistent only under $I(0)$ noise. To carry inference and produce confidence intervals, one must take a stand on whether the noise is $I(0)$ or $I(1)$; see Ref. 49. Given the overwhelming evidence presented above, all series are treated as having an $I(0)$ noise component. Nevertheless, we confirmed that this agrees with the empirical evidence. To verify item (1), we applied the Perron and Yabu test,[48] which indicates a rejection of the null hypothesis of no break in favor of one break (Table 1). As stated above, the estimate for LLRF is 1963 using the sample period 1880–1986 (to avoid a bias due to the hiatus, i.e., a second break in 1992). The prebreak slope is 0.0059 (SE: 8.22E-05) and the slope change is 0.0305 (SE: 0.0004). Using the same sample, the estimate for the break in global temperatures using the HadCRUT4 series is 1963 (95% CI: 1948–1978) with the prebreak slope being 0.0038 (SE: 0.0004) and the slope change 0.0076 (SE: 0.0022). For the NASA series the estimated break date is 1965 (95% CI: 1952–1978) with the prebreak slope being 0.0046 (SE: 0.0006) and the slope change 0.0166 (SE: 0.0033). This verifies items (2) and (3). Also, the Kim and Perron test[52] for a UR allowing for a break rejects the null hypothesis of an integrated noise component in favor of a stationary one. This applies to all series considered.

Note that for the HadCRUT4 series, the break date on a yearly scale is the same as that for LLRF. This is still consistent with having the break date in LLRF occur prior to the break date in CT since the causal effect can occur within a year. In fact, with the large standard errors in the estimates of the break dates in the temperatures series (given the high noise compared to that for LLRF), one would expect that the break dates in LLRF and CT should not be statistically different from each other. This is indeed the case. First, Ref. 8 showed, using the co-trending test of Bierens,[53] that various measures of temperatures and radiative forcings have a common (nonlinear) trend, which implies that the breaks have to be nearly common (in a statistical sense that accounts for the noise in the data). Also, Ref. 21 devised direct tests for common breaks in joint-segmented trend models and concluded that the breaks in various measures of temperatures and forcings are common. Standard physics for climate change processes

Table 3. Parameter values used for the simulation experiment to estimate the rejection rates of the Granger causality test applied to LLFR and CT, sample 1880–1986

	T_B	α	c	b	δ	σ_e^2
LLRF	1963	0	0.001318	0.005938	0.030521	0.0005
CT	1965	0.375235	–0.417209	0.004622	0.016627	0.0156

NOTE: The parameter values correspond to a broken linear term of the form $c + bt + \delta 1(t > T_B)(t - T_B) + u_t$, where $u_t = au_{t-1} + e_t$ and $e_t \sim$ i.i.d. $N(0, \sigma_e^2)$. T_B is the date of the break in the slope of the trend function.

suggest that common breaks should be interpreted as having the break in LLRF occur slightly prior to that in CT, consistent with the evidence presented here.

Implications for standard GC tests

The main issue from above is that for LLRF_t deviations from trend are essentially null. This implies that causality results obtained using standard methods, as described above, should be interpreted in a different way. This holds true whether the series is characterized as being TS or integrated for the following reasons. If the series are TS, the test based on specification (2) relies on assessing whether deviations from trends in LLRF_t can help predict deviations from trend in CT_t. However, the deviations from trend in LLRF_t are, essentially, 0. Hence, it should not be possible to reject the null hypothesis of no GC from LLRF to CT. Using the fitted trends for LLRF and CT (filtered HadCRUT and NASA) and the estimates of the break dates reported above, this is indeed the case irrespective of the number of lags used.

When adopting specification (3), the test relies on assessing whether past changes in LLRF_t can help predict the changes in CT_t. In this case, the changes in LLRF_t are, for all intents and purposes, constant, except for the different means before and after the abrupt increase in the growth rate in the 1960s, a mild decrease in the growth rate in the 1990s and minor variations in the 1940s. Accordingly, any finding of GC from LLRF to CT cannot be ascribed to the effect of variations in the series but should come solely (or mostly) from the presence of the breaks in the 1960s. To illustrate this issue related to specification (3), we conducted a small simulation experiment. We consider LLRF and CT as being generated by a broken linear trend model of the form $c + bt + \delta 1(t > T_B)(t - T_B) + u_t$, where $u_t = au_{t-1} + e_t$ and $e_t \sim$ i.i.d. $N(0, \sigma_e^2)$. The values of the parameters were obtained from the fitted trend from the data (using NASA for CT) and are given in Table 3. To obtain the rejection frequencies, we used 5000 simulations. The results from the simulation experiment show that the null of no GC from LLRF_t to CT_t is always rejected at the 5% significance level, while the null of no GC from CT_t to LLRF_t is rejected only about 8% of the times, which is close to the size of the test. This result is interesting because it shows that if the data are described as we claim they are, one is bound to find evidence of GC using standard methods. Hence, our results are encompassing in that they can explain prior findings reported in the literature. The interpretation is, however, quite different and stems solely from the presence of locally ordered breaks. The noise components can be completely independent.

Conclusions

We presented a purely statistical observations-based model-free analysis that provides evidence about GC from LLRF to the CT. This relies on having locally ordered breaks in the slope of the trend functions of LLRF and the CT, with the break for LLRF occurring before that for the CT and with the slope changes being of the same sign. The empirical evidence indicates that these conditions are satisfied empirically using standard global surface temperature series and an aggregate measure of LLRF (CO_2, N_2O, and CFCs). We also discussed why the presence of broken trends could lead one to conclude in favor of GC when using standard methods even if the noise function in LLRF is negligible. We showed why breaks in the trend function could be used to identify causality properties. The arguments are deceptively simple, yet quite compelling.

Competing interests

The authors declare no competing interests

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