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ORIGINAL PAPER

# Testing for linear Granger causality from natural/anthropogenic forcings to global temperature anomalies

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**Abstract** In this paper, we analyze the Granger causality from natural or anthropogenic forcings to global temperature anomalies. The lag-augmented Wald test is performed, and its robustness is also evaluated considering bootstrap method. The results show there is no-evidence of Granger causality from natural forcings to global temperature. On the contrary, a detectable Granger causality is found from anthropogenic forcings to global temperature confirming that greenhouse gases have an important role on recent global warming.

## 1 Introduction

A current global problem is the role of the human contribution on climate changes. In fact, greenhouse gases seem to have a relevant impact on global surface temperature's rise. Global warming may be also caused by natural forcing as solar or volcanic activities. Thus, the relationships between global surface temperature and natural or anthropogenic forcings have been the most important subjects of research in the last decades. The studies are often performed by means of Granger causality (GC) that is about an incremental forecasting power. In particular, a variable $x$ Granger cause a variable $y$ if the forecasts of $y$ can be improved by means of $x$. Sun and Wang (1996) provide evidence of GC from $CO_2$ emission to global temperature. Kaufmann and Stern (1997) suggest that human activity has played a role in the historical record of temperature. A study by Triacca (2001), a follow-up on Kaufmann and Stern, shows other conclusions obtained from the results of Kaufmann and Stern. Triacca (2005), using Toda and Yamamoto's method (Toda and Yamamoto 1995), evidences that there is no Granger causality between atmospheric concentration of carbon dioxide and global temperature. Elsner (2007) finds GC from global temperature to Atlantic sea surface temperature, confirming the theory that climate change influences hurricane intensity, considering that changes in global temperature are due to anthropogenic forcings. Recently in Kodra et al. (2011), a detectable Granger causality from $CO_2$ to global temperature is explained. The authors also perform an out-of-sample study in order to give more evidence for their in-sample results. The out-of-sample results are based only on descriptive statistical indices, and we do not know if out-of-sample Granger causality is statistically significant. In Attanasio et al. (2012), out-of-sample Granger noncausality tests are performed from anthropogenic or natural forcings to global temperature. The study evidences the rejection of the null hypothesis of Granger noncausality when greenhouse gases are used, whereas Granger causality is not found from natural forcings to global temperature. Other results (Mokhov and Smirnov 2008; Reichel et al. 2001), using in-sample tests, evidence the influence of solar activity on the global surface temperature.

The different results may depend on the models adopted in the analysis, or whether the tests are in-sample or out-of-sample. In particular, in-sample analysis depends on time series characteristics, and there is often the possibility of overfitting. In fact, significant in-sample Granger causality does not guarantee significant out-of-sample predictability. Out-of-sample tests

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are often recommended because they may stress the true forecasting ability of one variable for another, and the results are more robust in terms of overfitting (Chao et al. 2001; Clark 2004; Gelper and Croux 2007). Differently, Inoue and Kilian (2004) find the results of in-sample tests more credible than those of out-of-sample tests.

This paper is a follow-up of Attanasio et al. (2012). Here, we consider in-sample Granger noncausality test using the same dataset to investigate the possible differences between in-sample or out-of-sample results. The paper is organized as follows: a review of Granger causality is given in the next section. We present the data in Section 3. A preliminary study of the time series is explained in Section 4. Results of Granger causality analysis are discussed in Section 5, and a brief conclusion is drawn in Section 6.

## 2 Granger causality methodology

Granger (1969) has defined a concept of causality very useful in econometric research. Let $I_t^{x,y} = \{x_0, \ldots, x_t, y_0, \ldots, y_t\}$ be the information set. We will say that the variable $x$ Granger cause the variable $y$ if the mean square error of the best predictor of $y_{t+1}$ based on $I_t^{x,y}$ is smaller than the mean square error of the best predictor of $y_{t+1}$ that uses $I_t^y = I_t^{x,y} - \{x_s, s \leq t\}$. Before testing for Granger causality, it is important to establish the properties of the time series involved in the analysis, because the use of nonstationary time series can involve spurious causality results (Stock and Watson 1989; Sims et al. 1990). In this paper, the lag-augmented Wald test is applied (Toda and Yamamoto 1995) that is robust to the integration and possible cointegration properties of the variables. In fact, it is applicable if the variables are stationary, integrated or cointegrated of an arbitrary order. The procedure requires only the knowledge of the maximum order of integration of the series.

We consider two nested models, the unrestricted regression model

$$y_t = \mu_1 + \sum_{j=1}^{k} \alpha_j y_{t-j} + \sum_{j=1}^{k} \psi_j x_{t-j} + \varepsilon_t \tag{1}$$

and the restricted model

$$y_t = \mu_2 + \sum_{j=1}^{k} \beta_j y_{t-j} + u_t \tag{2}$$

where $\mu_1$ and $\mu_2$ are constants, $\alpha$, $\psi$, and $\beta$ are the coefficients of the models, $\varepsilon_t$ and $u_t$ are univariate white noise, and $k$ is the order of the models. If $(\psi_1, \ldots, \psi_k)$, in Eq. 1, is equal to the zero vector, then $x$ does not Granger-cause $y$. The null hypothesis of noncausality corresponds to

$$H_0 : \psi_1 = \psi_2 = \ldots = \psi_k = 0\,. \tag{3}$$

Estimating the parameters of the models (1) and (2) by ordinary least squares (OLS), the significance of this restriction is evaluated by the test statistics $F$,

$$F = \frac{(\mathrm{RSS_r} - \mathrm{RSS_u})\,/q}{\mathrm{RSS_u}/(T-m)} \tag{4}$$

where $\mathrm{RSS_r}$ is the residuals sum of square of restricted model (2), $\mathrm{RSS_u}$ is the residuals sum of square of unrestricted model (1), $q$ is the number of coefficients restricted to zero ($q = k$), $m$ is the number of coefficients of the unrestricted model ($m = 2k + 1$), and $T$ is the number of observations. Under the assumption that the time series are stationary, the test statistics in Eq. 4 asymptotically has a $F(q, T - m)$ distribution under $H_0$. A significant statistics implies that the null hypothesis of noncausality is rejected.

When the time series are not stationary, the standard asymptotic theory cannot be employed because the test statistics $F$ in Eq. 4 has a nonstandard distribution (Sims et al. 1990). Toda and Yamamoto (1995) propose to overfit the unrestricted model (1) by $d$ extra lags, where $d$ is the maximum order of integration of $x_t$ and $y_t$, in order to test the null hypothesis (3). In fact, if the true data generation process is Eq. 1, then the model

$$y_t = \mu_1 + \sum_{j=1}^{k} \alpha_j y_{t-j} + \sum_{j=1}^{k} \psi_j x_{t-j} + \sum_{j=k+1}^{k+d} \left(\alpha_j y_{t-j} + \psi_j x_{t-j}\right) + \varepsilon_t$$

with $\alpha_{k+1} = \ldots = \alpha_{k+d} = \psi_{k+1} = \ldots = \psi_{k+d} = 0$ describes the data-generating process equally well. In particular, we should point out that the parameters of the extra lags, $\{\psi_j\}_{j=k+1}^{k+d}$, are unrestricted in testing for Granger causality from $x$ to $y$ because they are zero by assumption. The null hypothesis of noncausality is always as in Eq. 3. Therefore, this hypothesis can be tested considering the unrestricted model

$$y_t = \mu_1 + \sum_{j=1}^{k+d} \alpha_j y_{t-j} + \sum_{j=1}^{k+d} \psi_j x_{t-j} + \varepsilon_t \tag{5}$$

and the restricted model

$$y_t = \mu_2 + \sum_{j=1}^{k+d} \beta_j y_{t-j} + \sum_{j=k+1}^{k+d} \gamma_j x_{t-j} + u_t\,. \tag{6}$$

The coefficients of the two models are estimated by means of OLS, and the test statistics became

$$F = \frac{(\mathrm{RSS_r} - \mathrm{RSS_u})\,/\,k}{\mathrm{RSS_u}/(T-(2k+2d+1))} \tag{7}$$

where here, $\mathrm{RSS_r}$ is the residuals sum of square of restricted model (6) and $\mathrm{RSS_u}$ is the residuals sum of square of unrestricted model (5). Toda and Yamamoto (1995) show the test statistics (Eq. 7) asymptotically has a standard distribution $F(k, T-2k-2d-1)$. So the function of the extra coefficients is only to guarantee the use of asymptotical distribution theory.

We know the lag-augmented Wald test can suffer from size distortion and low power especially for small samples. Then the bootstrap method is often used to determine the robustness of Granger causality results (Giles 1997; Hacker and Hatemi-J 2006; Hatemi-J and Shukur 2002; Lukasz 2010; Mantalos 2000; Mavrotas and Kelly 2001; Shukur and Mantalos 2000). Thus the following bootstrap scheme is applied:

1. Considering the $d$ extra lags, estimate the parameters of the unrestricted and restricted models in Eqs. 5 and 6 and calculate the statistics $F$ as in Eq. 7.
2. Under the null hypothesis of noncausality and without the $d$ extra lags, estimate the parameters $\mu_2$ and $\{\beta_j\}_{j=1}^{k}$ of the restricted model (2) and calculate the residuals $\hat{u}_t$.
3. Apply bootstrap procedure (resampling with replacement) on $\hat{u}_t$ and obtain the pseudo-residuals $u_t^*$.
4. Create the pseudo-data $y_t^*$ given by

$$y_t^* = \hat{\mu}_2 + \sum_{j=1}^{k} \hat{\beta}_j y_{t-j}^* + u_t^* \tag{8}$$

5. Using the pseudo-data $y_t^*$, repeat the steps 1 and calculate the $F$ bootstrap statistics.
6. Execute steps from 3 to 5 for $N$ times.
7. Calculate the bootstrap $p$ value which is the proportion of the $F$ estimated bootstrap statistics that exceed the same statistic evaluated on the observed data.

In our application, the bootstrap $p$ value is calculated using $N = 10,000$.

## 3 Data

Here, we deal with the following annual time series:

- Global temperature anomalies $y_t$: data available at http://www.cru.uea.ac.uk/cru/data/;
- $CO_2$, $CH_4$, and $N_2O$: data available at http://data.giss.nasa.gov. We have used IPCC (2001) expressions to convert greenhouse gas changes to instantaneous radiative forcing. In particular, $c_t$ is $CO_2$ radiative forcing (RF), $m_t$ is $CH_4$ RF, and $n_t$ is $N_2O$ RF;
- Total solar irradiance $\mathrm{TSI}_t$: data available at www.geo.fu-berlin.de;
- Cosmic ray intensity $\mathrm{CRI}_t$: data available at ftp.ncdc.noaa.gov;
- Stratospheric aerosol optical thickness (SAOT) at 550 nm $\mathrm{SAOT}_t$: data available at http://data.giss.nasa.gov;

The period of study ranges from 1850 to 2007. We are interested in testing Granger causality from the single forcing to global temperature anomalies. Using the same approach of Kodra et al. (2011), we apply Granger noncausality tests for the last 58, 68, 78, 88, 98, 108, 118, 128, 138, 148, and 158 observations of our series. In this way, we may observe the influence of greenhouse gases or natural forcings to global temperature's rise. In particular, we also analyze Granger causality from global radiative forcing $g_t$ $(g_t = c_t + m_t + n_t)$ to global temperature.

## 4 Unit root tests on global temperature anomalies and forcings

In order to apply lag-augmented Wald test, the order of integration of the series is required. In particular, a time series $w_t$ is integrated of order $h$ $(w_t \sim I(h))$ if $\Delta^h w_t$ is stationary, where $\Delta^r w_t$ is nonstationary for $r < h$. In this section, we focus on the presence or absence of stochastic trends in the global temperature anomalies and forcings employing the augmented Dickey–Fuller test (Dickey and Fuller 1981).

The model of the augmented Dickey–Fuller (ADF) test is specified as follows:

$$\Delta w_t = q_0 + q_1 t + \varphi w_{t-1} + \sum_{j=1}^{p^*} \xi_j \Delta w_{t-j} + v_t \tag{9}$$

where $v_t$ is a white noise. The lagged first differences of the dependent variables provide a correction for possible serial correlation. If $\varphi = 0$ and $q_1 = 0$, then $w_t$ has a unit root and a stochastic linear trend. Alternatively, if $\varphi < 0$, then the series is linear trend stationary. The null hypothesis is that the series is nontrend stationary. The ADF statistics is

$$ADF_t = \frac{\hat{\varphi}}{se(\hat{\varphi})} \tag{10}$$

where $\hat{\varphi}$ is the OLS estimate of $\varphi$, and $se(\hat{\varphi})$ is the $\hat{\varphi}$'s standard error. The critical values are not standard, and

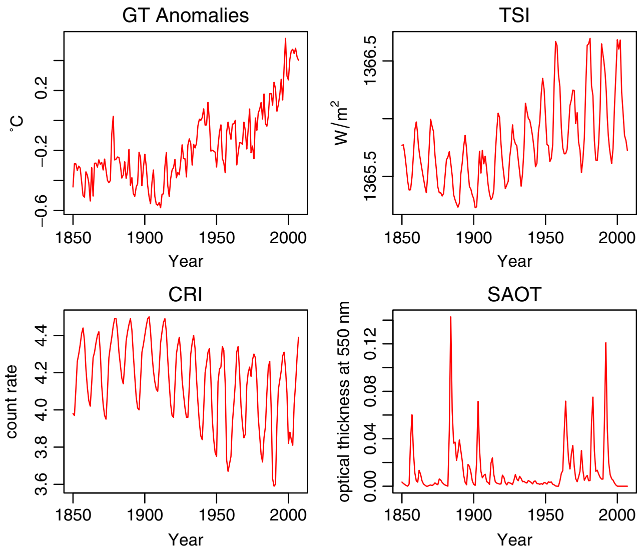


**Fig. 1** Plots of global temperature anomalies (*GT anomalies*, unit in degrees Celsius), total solar irradiance (*TSI*, unit in watts per square meter), cosmic ray intensity (*CRI*, unit in count rate of a polar neutron monitor), and stratospheric aerosol optical thickness at 550 nm (*SAOT*, unit in optical thickness at 550 nm)

they depend on the deterministic component selected in Eq. 9. The value of $p^*$, where $p^*$ is the model order, is selected between 0 and 10 using Akaike information criteria given by

$$\mathrm{AIC}(p^*) = \ln\left(\hat{\sigma}_v^2(p^*)\right) + \frac{2\,(p^* + l)}{T} \tag{11}$$

where $\hat{\sigma}_v^2(p^*) = T^{-1}\sum_{t=1}^{T}\hat{v}_t^2$ is the error variance estimator based on the OLS residuals $\hat{v}_t$ of the model (9), and $l$ is the number of deterministic components.

The deterministic component in Eq. 9 is chosen, observing the graphic of the time series. In our cases, we consider linear trend and constant for the original series $w_t$, constant for the first difference $\Delta w_t$, and without trend and constant for the second difference $\Delta^2 w_t$. Only for $\mathrm{SAOT}_t$ the deterministic component is taken constant for the original series.

Haldrup and Lildholdt (2002) find that when $w_t$ is $I(2)$, the ADF statistics gives rise to excessive rejection of the unit root null in favor of the stationary alternative. It depends on the ADF statistics which has a different distribution caused by the extra unit root. The authors suggest to test $I(2)$ against $I(1)$ prior to testing $I(1)$ against $I(0)$. Using the same approach described in Lutkepohl and Kratzig (2004), if $w_t$ can be $I(2)$, a unit root test is applied to $\Delta^2 w_t$ first. If the null hypothesis is rejected, a unit root test is applied to $\Delta w_t$. If the null hypothesis of unit root cannot be rejected in $\Delta w_t$, then the time series $w_t$ is $I(2)$; otherwise, considering $w_t$ as an $I(2)$ series is not a good choice, and we test $I(1)$ against $I(0)$. In this last case, a unit root test is applied to $w_t$.

## 4.1 Unit root test outcomes

The graphic of global temperature (Fig. 1) shows this time series may be $I(1)$. Therefore, the original series $y_t$ is tested. The ADF test suggests that global temperature is $I(1)$. This result is also one of the principal conclusions of recent researches (Kaufmann and Stern 1997; Kodra et al. 2011; Liu and Rodriguez 2005; Stern and Kaufmann 1999). Then we conclude that $y_t$ has a stochastic trend.

The time series $\mathrm{TSI}_t$ and $\mathrm{CRI}_t$ (Fig. 1) have a periodicity of 11 years approximately. This is confirmed by means of a spectral analysis based on Bartlett estimator. The total solar irradiance and the cosmic ray intensity are $I(1)$, whereas the time series $\mathrm{SAOT}_t$ is stationary. The results are shown in Table 1. Thus, the maximum order of integration between global temperature and the single natural forcing is $d = 1$.

The plots of radiative forcings (Fig. 2) indicate these time series may be $I(2)$. Therefore, the second difference is tested first. ADF test suggests radiative forcings are $I(2)$ (Table 1). Greenhouse gases have

**Table 1** ADF test for global temperature anomalies $y_t$, TSI, CRI, SAOT, carbon dioxide RF $c_t$, methane RF $m_t$, nitrous oxide RF $n_t$, and global RF $g_t$

| Time series | ADF statistics | ADF $p^*$ | Critical value (5 %) | Conclusion |
|---|---|---|---|---|
| $y_t$ | −2.25 | 3 | −3.45 | $I(1)$ |
| $\mathrm{TSI}_t$ | −2.17 | 8 | −3.45 | $I(1)$ |
| $\mathrm{CRI}_t$ | −2.35 | 8 | −3.45 | $I(1)$ |
| $\mathrm{SAOT}_t$ | −5.31 | 2 | −2.89 | $I(0)$ |
| $\Delta^2 c_t$ | −9.07 | 5 | −1.95 | $I(0)$ |
| $\Delta c_t$ | −0.35 | 6 | −2.89 | $I(1)$ |
| $\Delta^2 m_t$ | −2.29 | 8 | −1.95 | $I(0)$ |
| $\Delta m_t$ | −2.11 | 9 | −2.89 | $I(1)$ |
| $\Delta^2 n_t$ | −9.39 | 6 | −1.95 | $I(0)$ |
| $\Delta n_t$ | 0.40 | 7 | −2.89 | $I(1)$ |
| $\Delta^2 g_t$ | −8.55 | 5 | −1.95 | $I(0)$ |
| $\Delta g_t$ | −0.64 | 6 | −2.89 | $I(1)$ |

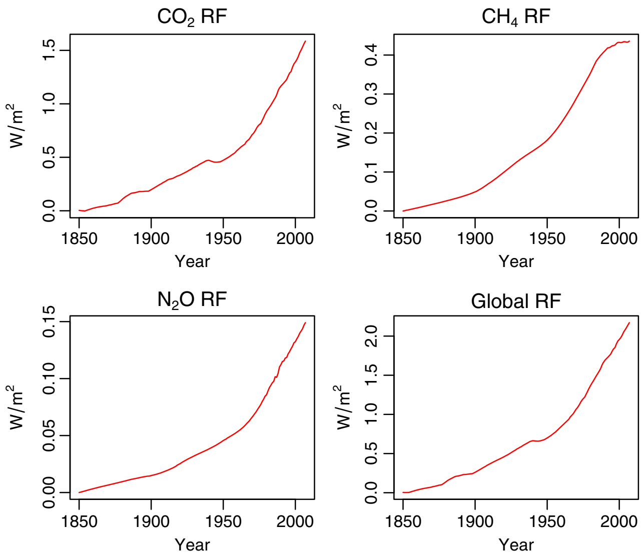


**Fig. 2** Plots of carbon dioxide radiative forcing ($CO_2\ RF$), methane radiative forcing ($CH_4\ RF$), nitrous oxide radiative forcing ($N_2O\ RF$), and global radiative forcing (*Global RF*). Units in watts per square meter

been found to have one unit root (Kaufmann and Stern 1997; Stern and Kaufmann 1999), then there is not a clear drawing about the order of integration of these series. Considering that $y_t$ is integrated of order one, we have two possible combinations: $y_t \sim I(1)$ and radiative forcing $I(1)$, and $y_t \sim I(1)$ and radiative forcing $I(2)$. In the first case, the maximum order of integration $d$ is equal to 1; otherwise, $d = 2$. Which value of $d$ do we select to apply the methodology of Toda and

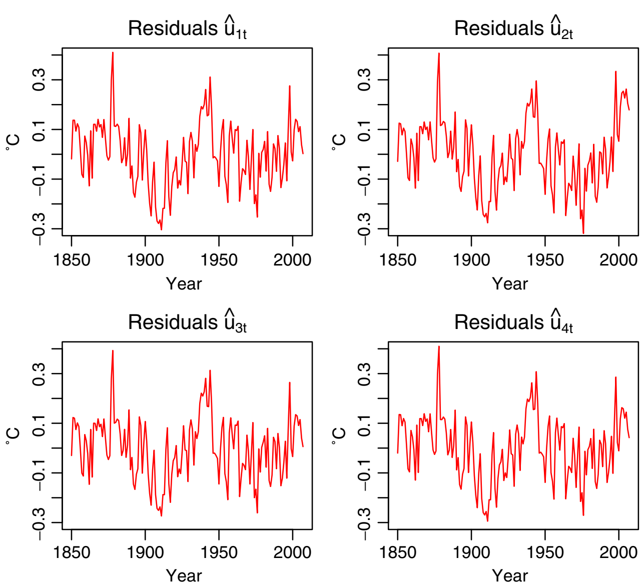


**Fig. 3** Graphs of the residuals $\hat{u}_{1t}$, $\hat{u}_{2t}$, $\hat{u}_{3t}$, and $\hat{u}_{4t}$. Units in degrees Celsius

**Table 2** ADF test for the residuals $\{\hat{u}_{it}\}_{i=1}^{4}$

| Time series | ADF statistics | Critical value (5 %) | Conclusion |
|---|---|---|---|
| $\hat{u}_{1t}$ | $-6.26$ | $-3.42$ | $I(0)$ |
| $\hat{u}_{2t}$ | $-5.68$ | $-3.42$ | $I(0)$ |
| $\hat{u}_{3t}$ | $-6.52$ | $-3.42$ | $I(0)$ |
| $\hat{u}_{4t}$ | $-6.21$ | $-3.42$ | $I(0)$ |

Yamamoto? We can perform this method considering $d = 1$ and $d = 2$ as in Triacca (2005). We observe an interesting notice. Let us consider the residuals of the following regression models:

- $y_t = \vartheta_1 + \phi_1 c_t + u_{1t}$;
- $y_t = \vartheta_2 + \phi_2 m_t + u_{2t}$;
- $y_t = \vartheta_3 + \phi_3 n_t + u_{3t}$;
- $y_t = \vartheta_4 + \phi_4 g_t + u_{4t}$.

In Fig. 3, the plots of $\hat{u}_{it}$ are shown, for $i = 1, 2, 3, 4$. Graphic analysis suggests these residuals are stationary. Also, the ADF (Table 2), with $p^* = 0$, recommends $u_{it} \sim I(0)$, $i = 1, 2, 3, 4$. As described in Hamilton (1994), ADF test statistics is constructed as in Eq. 9 without constant and trend but the critical values are different because the test is applied to the residuals $\hat{u}_{it}$ from a spurious regression (Phillips and Ouliaris 1990). Therefore, $\hat{u}_{it}$ is a stationary linear combination of $y_t$ and radiative forcing, then these two series are of the same order of integration. Observing the previous two combinations, the only choice is that global temperature and the respective radiative forcing are $I(1)$. In this way, we have also found an important structure of our series. In fact, global temperature and radiative forcing are cointegrated (Engle and Granger 1987; Granger 1981), so there is a long-run equilibrium relationship tying the individual series together. Therefore, the existence of a cointegrating relationship suggests that there must be a Granger causality in at least one direction (Granger 1988), but it does not indicate the direction of temporal causality between the variables.

## 5 Granger causality results

In the previous section, we have analyzed the order of integration of global temperature and forcings. We have found that the maximum order of integration is always equal to 1. Granger noncausality tests are performed for $k = 1$, $k = 2$, and $k = 3$ in Eqs. 1 and 2. In this way, the models are parsimonious, and the residuals are always uncorrelated. Therefore, the mean of bootstrapped residuals is zero.

Here, Granger causality is studied between different sets of two series. Of course, a multivariate approach

**Table 3** Results of causality test ($p$ values) from total solar irradiance to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.164 | 0.165 | 0.346 | 0.155 | 0.156 | 0.326 |
| 1940–2007 | 0.329 | 0.253 | 0.425 | 0.312 | 0.230 | 0.417 |
| 1930–2007 | 0.239 | 0.238 | 0.417 | 0.223 | 0.225 | 0.418 |
| 1920–2007 | 0.153 | 0.134 | 0.276 | 0.148 | 0.138 | 0.296 |
| 1910–2007 | 0.277 | 0.218 | 0.377 | 0.270 | 0.220 | 0.409 |
| 1900–2007 | 0.270 | 0.253 | 0.369 | 0.259 | 0.258 | 0.405 |
| 1890–2007 | 0.227 | 0.196 | 0.208 | 0.226 | 0.206 | 0.252 |
| 1880–2007 | 0.235 | 0.200 | 0.219 | 0.230 | 0.213 | 0.262 |
| 1870–2007 | 0.264 | 0.265 | 0.338 | 0.259 | 0.271 | 0.389 |
| 1860–2007 | 0.302 | 0.287 | 0.396 | 0.292 | 0.296 | 0.444 |
| 1850–2007 | 0.222 | 0.208 | 0.294 | 0.222 | 0.214 | 0.342 |

[a] Significant at the 5 % level

**Table 4** Results of causality test ($p$ values) from cosmic ray intensity to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.741 | 0.655 | 0.745 | 0.734 | 0.645 | 0.741 |
| 1940–2007 | 0.661 | 0.502 | 0.546 | 0.663 | 0.481 | 0.535 |
| 1930–2007 | 0.389 | 0.398 | 0.494 | 0.377 | 0.391 | 0.496 |
| 1920–2007 | 0.368 | 0.342 | 0.464 | 0.361 | 0.329 | 0.460 |
| 1910–2007 | 0.454 | 0.418 | 0.591 | 0.447 | 0.411 | 0.597 |
| 1900–2007 | 0.387 | 0.12 | 0.333 | 0.372 | 0.212 | 0.350 |
| 1890–2007 | 0.236 | 0.102 | 0.155 | 0.227 | 0.105 | 0.170 |
| 1880–2007 | 0.251 | 0.066 | 0.103 | 0.255 | 0.069 | 0.120 |
| 1870–2007 | 0.332 | 0.056 | 0.124 | 0.331 | 0.058 | 0.145 |
| 1860–2007 | 0.368 | 0.042[a] | 0.097 | 0.368 | 0.042[a] | 0.113 |
| 1850–2007 | 0.269 | 0.026[a] | 0.062 | 0.269 | 0.030[a] | 0.081 |

[a] Significant at the 5 % level

**Table 5** Results of causality test ($p$ values) from stratospheric aerosol optical thickness at 550 nm to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.135 | 0.187 | 0.210 | 0.131 | 0.183 | 0.198 |
| 1940–2007 | 0.184 | 0.315 | 0.478 | 0.178 | 0.322 | 0.480 |
| 1930–2007 | 0.156 | 0.251 | 0.360 | 0.162 | 0.257 | 0.369 |
| 1920–2007 | 0.163 | 0.278 | 0.376 | 0.166 | 0.283 | 0.387 |
| 1910–2007 | 0.218 | 0.416 | 0.560 | 0.222 | 0.418 | 0.575 |
| 1900–2007 | 0.120 | 0.219 | 0.350 | 0.119 | 0.229 | 0.367 |
| 1890–2007 | 0.070 | 0.125 | 0.217 | 0.073 | 0.126 | 0.227 |
| 1880–2007 | 0.078 | 0.119 | 0.159 | 0.081 | 0.117 | 0.159 |
| 1870–2007 | 0.108 | 0.156 | 0.189 | 0.109 | 0.166 | 0.187 |
| 1860–2007 | 0.109 | 0.153 | 0.204 | 0.112 | 0.158 | 0.207 |
| 1850–2007 | 0.059 | 0.082 | 0.124 | 0.059 | 0.080 | 0.117 |

[a] Significant at the 5 % level

**Table 6** Results of causality test ($p$ values) from $CO_2$ RF to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.051 | 0.011[a] | 0.012[a] | 0.060 | 0.015[a] | 0.018[a] |
| 1940–2007 | 0.002[a] | 0.005[a] | 0.012[a] | 0.005[a] | 0.011[a] | 0.028[a] |
| 1930–2007 | 0.004[a] | 0.008[a] | 0.016[a] | 0.006[a] | 0.015[a] | 0.034[a] |
| 1920–2007 | 0.003[a] | 0.007[a] | 0.013[a] | 0.005[a] | 0.014[a] | 0.022[a] |
| 1910–2007 | 0.002[a] | 0.009[a] | 0.010[a] | 0.003[a] | 0.016[a] | 0.019[a] |
| 1900–2007 | 0.001[a] | 0.007[a] | 0.010[a] | 0.001[a] | 0.015[a] | 0.022[a] |
| 1890–2007 | 0.001[a] | 0.005[a] | 0.013[a] | 0.001[a] | 0.011[a] | 0.020[a] |
| 1880–2007 | 0.007[a] | 0.018[a] | 0.021[a] | 0.012[a] | 0.029[a] | 0.033[a] |
| 1870–2007 | 0.010[a] | 0.015[a] | 0.015[a] | 0.017[a] | 0.025[a] | 0.022[a] |
| 1860–2007 | 0.010[a] | 0.016[a] | 0.018[a] | 0.015[a] | 0.024[a] | 0.028[a] |
| 1850–2007 | 0.008[a] | 0.014[a] | 0.015[a] | 0.012[a] | 0.022[a] | 0.024[a] |

[a] Significant at the 5 % level

**Table 7** Results of causality test ($p$ values) from $CH_4$ RF to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.000[a] | 0.003[a] | 0.042[a] | 0.003[a] | 0.019[a] | 0.161 |
| 1940–2007 | 0.000[a] | 0.003[a] | 0.036[a] | 0.002[a] | 0.029[a] | 0.155 |
| 1930–2007 | 0.000[a] | 0.000[a] | 0.006[a] | 0.000[a] | 0.006[a] | 0.040[a] |
| 1920–2007 | 0.000[a] | 0.001[a] | 0.009[a] | 0.000[a] | 0.009[a] | 0.054 |
| 1910–2007 | 0.000[a] | 0.007[a] | 0.034[a] | 0.003[a] | 0.038[a] | 0.117 |
| 1900–2007 | 0.001[a] | 0.017[a] | 0.078 | 0.007[a] | 0.059 | 0.187 |
| 1890–2007 | 0.001[a] | 0.012[a] | 0.051 | 0.004[a] | 0.043[a] | 0.129 |
| 1880–2007 | 0.000[a] | 0.007[a] | 0.034[a] | 0.002[a] | 0.032[a] | 0.094 |
| 1870–2007 | 0.000[a] | 0.004[a] | 0.026[a] | 0.001[a] | 0.017[a] | 0.067 |
| 1860–2007 | 0.000[a] | 0.001[a] | 0.010[a] | 0.001[a] | 0.008[a] | 0.036[a] |
| 1850–2007 | 0.000[a] | 0.001[a] | 0.008[a] | 0.000[a] | 0.006[a] | 0.029[a] |

[a] Significant at the 5 % level

**Table 8** Results of causality test ($p$ values) from $N_2O$ RF to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.620 | 0.634 | 0.079 | 0.643 | 0.677 | 0.121 |
| 1940–2007 | 0.473 | 0.672 | 0.060 | 0.497 | 0.710 | 0.096 |
| 1930–2007 | 0.399 | 0.634 | 0.048[a] | 0.422 | 0.673 | 0.078 |
| 1920–2007 | 0.381 | 0.648 | 0.038[a] | 0.399 | 0.678 | 0.062 |
| 1910–2007 | 0.376 | 0.595 | 0.035[a] | 0.398 | 0.633 | 0.052 |
| 1900–2007 | 0.391 | 0.558 | 0.036[a] | 0.407 | 0.588 | 0.052 |
| 1890–2007 | 0.356 | 0.537 | 0.031[a] | 0.374 | 0.564 | 0.042[a] |
| 1880–2007 | 0.333 | 0.498 | 0.032[a] | 0.347 | 0.525 | 0.047[a] |
| 1870–2007 | 0.299 | 0.495 | 0.048[a] | 0.318 | 0.516 | 0.063 |
| 1860–2007 | 0.300 | 0.478 | 0.063 | 0.313 | 0.497 | 0.073 |
| 1850–2007 | 0.307 | 0.469 | 0.057 | 0.323 | 0.482 | 0.075 |

[a] Significant at the 5 % level

**Table 9** Results of causality test ($p$ values) from global RF to global temperature, with $d = 1$, using Toda and Yamamoto (TY) and bootstrap methods

| Subperiod | TY | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | $k = 1$ | $k = 2$ | $k = 3$ | $k = 1$ | $k = 2$ | $k = 3$ |
| 1950–2007 | 0.014[a] | 0.006[a] | 0.011[a] | 0.025[a] | 0.014[a] | 0.026[a] |
| 1940–2007 | 0.001[a] | 0.002[a] | 0.007[a] | 0.003[a] | 0.007[a] | 0.025[a] |
| 1930–2007 | 0.001[a] | 0.003[a] | 0.010[a] | 0.001[a] | 0.009[a] | 0.026[a] |
| 1920–2007 | 0.001[a] | 0.002[a] | 0.008[a] | 0.003[a] | 0.007[a] | 0.025[a] |
| 1910–2007 | 0.001[a] | 0.003[a] | 0.007[a] | 0.001[a] | 0.009[a] | 0.016[a] |
| 1900–2007 | 0.000[a] | 0.003[a] | 0.005[a] | 0.002[a] | 0.008[a] | 0.013[a] |
| 1890–2007 | 0.000[a] | 0.002[a] | 0.006[a] | 0.000[a] | 0.006[a] | 0.011[a] |
| 1880–2007 | 0.002[a] | 0.007[a] | 0.011[a] | 0.004[a] | 0.012[a] | 0.021[a] |
| 1870–2007 | 0.001[a] | 0.005[a] | 0.007[a] | 0.003[a] | 0.009[a] | 0.014[a] |
| 1860–2007 | 0.001[a] | 0.004[a] | 0.007[a] | 0.002[a] | 0.008[a] | 0.012[a] |
| 1850–2007 | 0.001[a] | 0.003[a] | 0.005[a] | 0.004[a] | 0.004[a] | 0.009[a] |

[a] Significant at the 5 % level

(Gelper and Croux 2007) using models of higher dimension, as VAR models, could be envisaged in order to investigate the robustness of the bivariate results (Triacca 1998, 2002).

## 5.1 Natural forcings effect

It is clear in our results that there is no Granger causality from every natural forcings to global temperature. In fact, the null hypothesis of noncausality is never rejected exclusive of two cases for $CRI_t$. These outcomes are statistically robust because the $p$ values of the Toda and Yamamoto method are very similar to those of bootstrap method (Tables 3, 4 and 5). Furthermore, we have also analyzed the global effect of the natural forcings on global temperature, considering the variable $x_t$ in Eq. 1 as $x_t = (\mathrm{TSI, CRI, SAOT})_t$. Granger causality is never found[1] (with only one exception).

This evidence of Granger noncausality may depend on either linear models selected or in-sample tests. But Pasini et al. (2006), using neural network models, have shown that natural forcings have a weak nonlinear explanation on global temperature which does not permit to overcome the linear performance. Furthermore, in Attanasio et al. (2012), out-of-sample Granger causality is not found if natural forcings are used as regressors. These results confirm the low linear (or nonlinear) connection from natural forcings to global temperature.

## 5.2 Greenhouse gases effect

The results show that there is an evident Granger causality from $CO_2$ radiative forcing to global temperature (Table 6). In fact, using a 5 % significant level, we cannot reject the null hypothesis of noncausality from $CO_2$ RF to global temperature just in the first subperiod with $k = 1$. These outcomes are also confirmed by the bootstrap method.

Granger causality from $CH_4$ RF to global temperature is always detectable for $k = 1$ and $k = 2$ exclusive of one subperiod for the bootstrap scheme (Table 7). There are some differences for $k = 3$. In this case, the null hypothesis of Granger noncausality is not rejected in two subperiods employing standard Wald test and in eight subperiods using bootstrap method. Therefore, Granger causality of methane is less strong than Granger causality of carbon dioxide.

Instead, there is no detectable Granger causality from $N_2O$ radiative forcing to global temperature (Table 8). The statistics is always insignificant for $k = 1$ and $k = 2$, whereas we can often reject the null hypothesis of noncausality for $k = 3$ by means of the Toda and Yamamoto method. This does not mean that Granger causality is not an appropriate method for studying the causal relationship between these variables. In fact, this weak Granger causality can depend on the possible limitation of in-sample approach. In fact, a strong linear out-of-sample Granger causality exists from $N_2O$ to global temperature (Attanasio et al. 2012). In addition, linear model cannot often catch the relationship in the complex climate system because this relationship may be nonlinear. Recent studies have shown that anthropogenic variables have nonlinear connection (Attanasio and Triacca 2011; Pasini et al. 2006). Hence, we will consider other approaches or methods in future investigations in order to understand better the role of this greenhouse gas on temperature trend.

Global radiative forcing considers the global radiative forcings of carbon dioxide, nitrous oxide, and methane. It is interesting to understand the global impact of these gases on temperature using Granger causality. The outcomes show that there is a detectable Granger causality. In fact, the null hypothesis of noncausality is always rejected (Table 9), so a strong evidence of linear causality of $g_t$ on $y_t$ appears over all subperiods. It is an important outcome because it shows that the global contribution of greenhouse gases has a significant impact on the recent global warming.

# 6 Conclusion

In this paper, we have analyzed the interaction between external forcings and global temperature. The results stress that natural forcings do not Granger-cause global temperature. Among a number of man-made greenhouse gases, $CO_2$ has the greatest influence on the global climate. Granger causality from methane to global temperature is also evident, but it is less strong. Granger causality from nitrous oxide to global temperature is low because it depends on the model order selected; otherwise, the combined radiative forcing linearly Granger-cause global temperature. This important result proves that anthropogenic influences have a relevant role about the rise in global temperature.

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[1] The results are available from the author upon request.

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