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Human Activities and Global Warming: A Cointegration Analysis[1]

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Abstract

Do human activities indeed cause global warming? This paper attempts to answer this question by reexamining the time series properties of climate variables and the existence of long-run relationships between them. Double unit root testing shows that most of the radiative forcings of greenhouse gases are integrated of order two. We then apply an I(1) and I(2) cointegrating rank analysis to identify the presence of I(2) components. After identifying a linear combination of I(2) variables that cointegrates to an I(1) process, we proceed with the I(1) cointegrating analysis and we identify two possible cases with different rank specifications. Estimation of the equation for temperature suggests that this variable reacts significantly to the radiative forcings of greenhouse gases in the long-run. This evidence allow us to conclude that human activities affect temperature variations.

Keywords: Global Warming, Radiative Forcing, Cointegration, I(1) and I(2) Processes, Unit Roots.

JEL Classification: C22

Résumé

Est-ce que l'activité humaine entraîne effectivement le réchauffement du globe? Ce travail tente de répondre à cette question en ré-examinant les propriétés des séries chronologiques des variables climatiques, ainsi que la possibilité de l'existence à long terme d'une relation entre elles. Des tests de racines unitaires doubles démontrent que la variable qui représente la quantité de radiations causées par les gaz à effet de serre est intégrée d'ordre deux. Suite aux tests de racines unitaires, nous analysons la cointégration selon le rang pour des variables intégrés d'ordre I(1) et I(2) afin d'identifier la présence des composantes I(2). Après avoir identifié la combinaison linéaire de variables I(2) qui, par la cointégration résulte en un processus I(1), nous procédons à l'analyse de cointégration I(1) et nous identifions deux cas possibles avec des spécifications de rangs différentes. L'estimation de l'équation de la température nous amène à croire que cette variable réagie significativement aux radiations causées par les gaz à effet de serre à long terme. Les évidences nous permettent de conclure que l'activité humaine affecte les variations de la température.

Mots-clés: Réchauffement du globe, radiations, cointégration, processus I(1) et I(2), racines unitaires.

Code JEL: C22

1 Introduction

Although a large literature has contributed to the study of principal macroeconomic time series, in the area of climate change, application of new statistic tools is relatively new. In the last decade some attention has been paid to the properties of temperature and anthropogenic forcing time series and furthermore, to the possible causes of climate change. For example, Bloomfield and Nychka (1992), Woodward and Gray (1993, 1995) discussed if temperature time series contains a deterministic trend, using both frequency domain and time domain time series methods. A recent example about this issue is Fomby and Vogelsang (2001) finding evidence of global warming.

On the other hand, Kuo et al (1990), Schönwiese (1991), Schönwiese and Stähler (1991) and Tol and de Vos (1998) have examined the relation between air temperature and the atmospheric concentration of carbon dioxide. Whether carbon dioxide and global mean temperature (hereafter GMT) share a common stochastic trend was analyzed by Galbraith and Green (1993). Furthermore, Richard (1993) investigated more general causes of climate change by including carbon dioxide, sun irradiance and atmospheric aerosols time series in a causality test framework including temperature.

Recently, the nonstationary nature of the forcing factors has been addressed by Kaufmann and Stern (1997, 2002) and Stern and Kaufmann (1997, 1999, 2000). In fact, these authors have concentrated their analysis on three issues jointly with the use of the statistical tools related to them. These issues are: i) the analysis of the integration order of a set of variables including global temperature, greenhouse gases (hereafter GHGs), sun irradiance, stratospheric sulfates; ii) the analysis of causality and hemispheric temperature relations; and iii) the elaboration and estimation of a structural model to explain if human activities have altered global temperature. Unfortunately, the analysis of Stern and Kaufmann (1999) is not complete as a consequence of the complex nature of the different variables and the corresponding statistical tools needed. Precisely, on this aspect, one of the principal conclusions of Stern and Kaufman (1999) is that "....we have learned that the time series properties of the data are quite complex and may require the use of I(2) modelling as opposed to simpler I(1) approaches" (page 604). Furthermore, they recognize the necessity of using a full maximum likelihood estimation where modelling of all variables is allowed. In this paper we contribute to correct these two drawbacks using more appropriate statistical tools in identifying the degree of integration of the time series and using cointegration analysis with I(2) variables.

Stern and Kaufmann (1999) used the Augmented Dickey-Fuller (ADF hereafter) and found that some variables are possibly I(2) processes. However, Haldrup (1999) and Haldrup and Lildholdt (1999) pointed out that the application of ADF test to the levels and subsequently first-differences is not adequate for testing I(2) processes. These authors suggest using the procedure recommended by Hasza and Fuller (1979) and Dickey and Pantula (1987). Therefore, the first goal of this paper is to reexamine the time series properties of climate variable using the suggested test procedures. In the third section, we find that most gas variables are I(2) processes. The exception is $n2o_t$ where apparently an explosive root is present.

The issue of cointegration has been addressed by Kaufman and Stern (2002) but leaving I(2) variables out. In this paper we use the new framework proposed by Johansen (1992, 1995a, 1995b) and Paruolo (1996) which consists of identifying the I(1), I(2) cointegrating ranks and cointegrating vectors using a likelihood ratio statistic. As recommended by Juselius (1998), this approach should be complemented with the analysis of the number of eigenvalues close to the unit circle that are present in the companion matrix. The most convenient way to proceed is to identify a linear combination of the I(2) series that reduces the cointegrating space to an I(1) space so that standard I(1) cointegration analysis (Johansen, 1988, 1995b) may be performed. This is how Fiess and MacDonald (2001) proceeds and we will follow the same strategy[3]. In the I(1) framework, we identify two different cases according to the number of cointegrating vectors. Both vectors include temperature, sun irradiance, first differences of the I(2) variables and a linear combination of I(2) variables. Cointegrating vectors identified in this step are then used in the estimation of the error correction model, which shows a significant impact of GHGs on GMT.

The rest of this paper is organized as follows. Section 2 describes the data used in the empirical analysis. Section 3 presents testing procedures and discusses the principal results. Section 4 deals with cointegration methodology and gives results obtained from its application. Section 5 concludes. Tables and figures are presented at the end of the paper.

2 Description of the data

The data used in this paper include the time series of global mean temperature deviation (denoted by *temp*), the concentration of methane (ch_4),

[3] Other examples of identification and hypothesis testing in an $I(2)$ framework are Kongsted (1998) and Rahbek, Kongsted and Jorgensen (1999).

nitrous dioxide ($n2o$), carbon dioxide (co_2), chlorofluorocarbons (cfc_{11} and cfc_{12}). All data are from the web site of Goddard Institute for Space Studies available at www.giss.gov. In a first stage, we need to transfer the concentration of GHGs into radiative forcing[4], which affects the temperature directly and indirectly. The formulae are tabulated in the Intergovernmental Panel of Climate Change (IPCC, 2001). The radiative forcing of GHGs (at time t) are denoted as $rfch_{4t}$, $rfn2o_t$, $rfco_{2t}$, rfc_{11t} and rfc_{12t}.

To get a flavor of the shape of climate time series, level of the variables are graphed in Figure 1. As the radiative forcing of GHGs is smoother than the temperature time series, it is likely that they have higher integration order than GMT, which was found to be I(2) by the ADF test in Kaufmann and Stern (2002).

3 Testing for Unit Roots

Suppose we have the following data generating process,

$$A(L)y_t = d_t + u_t \tag{1}$$

where $d_t = \psi' z_t$, and z_t is a set of deterministic components denoted by $z_t = \{1\}$ when an intercept is present, or $z_t = \{1, t\}$ when both an intercept and a linear time trend are present. The noise function u_t follows a stationary $ARMA$ process and L denotes the lag operator with $Ly_t = y_{t-1}$.

Suppose that $A(L) = (1 - \alpha_1 L)(1 - \alpha_2 L)$ where α_1 and α_2 are the autoregressive parameters. When $|\alpha_1|$, $|\alpha_2| < 1$, the roots of the polynomial equation $A(L) = 0$ lie outside of the unit circle, then y_t is stationary, When $|\alpha_1| = 1$, $|\alpha_2| < 1$, y_t has one unit root and is denoted as I(1). When $|\alpha_1| = |\alpha_2| = 1$, y_t has two unit roots, which is denoted as I(2). If $|\alpha_1|$, $|\alpha_2| > 1$, y_t is an explosive process.

To verify if y_t is I(0), I(1), I(2) or explosive, the most widely used test is the statistics proposed by Dickey and Fuller (1979) which was extended by Said and Dickey (1984) to account for the correlation in the noise function and is denoted as ADF. The test statistic is based on the following OLS regression

[4] Radiative forcing is the change of the net irradiance caused by factors such as GHGs, water vapor, solar radiation. GHGs are of particular interest, as they are most likely to change raidative forcing over the next decade. The net irradiance is the difference of the irradiance that the earth absorbed minus the irradiance the the earth emitted, expressed in Wm^{-2}, where W is a measure of energy (Watt) and m indicates meters.

$$\Delta y_t = \psi' z_t + (\alpha - 1) y_{t-1} + \sum_{i=1}^{k} b_i \Delta y_{t-i} + u_t \tag{2}$$

where k is usually unknown. To select this parameter, we use the sequential data-dependent method based on the significance of the t-statistics of the last lag, which was recommended by Campbell and Perron (1991) and further analyzed by Ng and Perron (1995). That is, we start from a maximal lag k ($kmax$) and we verify if the t-statistic of the last lag on the first differences is significant at 10.0%. If it is not the case, we run the regression with $kmax - 1$ lags. The procedure stops when we find a significant lag. If none of the lags are significant, we choose $k = 0$. On the other hand, if the procedure selects the $kmax$, we increase the $kmax$ by one.

Our results from the application of a standard ADF test are similar to those obtained in Stern and Kaufmann (1997). Some time series are possibly I(2) processes. But according to Dickey and Pantula (1987), the limiting distribution of the t-statistics in the presence of the second unit root is not the usual Dickey-Fuller distribution. Therefore the rejection probability of H_0: $\alpha_1 = 1$ is dependent on the actual value of the second root α_2. Dickey and Pantula (1987) conducted a small scale Monte-Carlo experiment where they found size distortions. As a result, the ADF test rejects the null of one unit root too often in favor of stationarity when the time series is I(2) compared to it is I(1)[5]. To deal with this problem, Dickey and Pantula (1987) suggested a simple backward sequential procedure which we will use below.

Another issue related to the ADF testing for I(2) process is pointed by Haldrup and Lildholdt (1999). It extended the findings of Dickey and Pantula (1987) by examining the rejection probabilities of a single unit root against both stationary and explosive alternatives when two unit roots are present. They used sample size from 50 to 500 and found that the ADF test has a even bigger size distortion when tested against explosive alternative. In contrast, their simulation results showed that the procedure proposed by Dickey and Pantula has a controllable size distortion against both stationary and explosive alternatives.

The Dickey and Pantula test procedure for I(2) process is to reverse the sequence of the standard ADF test. The first step is to test the null hypothesis of two unit roots against the alternative of only one single unit

[5] This result is surprising because intuitively we should strongly reject stationarity when two unit roots are present rather than just one single unit root.

root. The test is based on the following regression

$$\Delta^2 y_t = (\alpha_1 - 1)y_{t-1} + (\alpha_2 - 1)\Delta y_{t-1} + \sum_{i=1}^{p-2} \varphi_j \Delta^2 y_{t-i} + \psi' z_t + u_t \qquad (3)$$

In both null and alternative hypothesis, at least one unit root is present. Thus by imposing $\alpha_1 = 1$, equation (3) becomes:

$$\Delta^2 y_t = (\alpha_2 - 1)\Delta y_{t-1} + \sum_{i=1}^{p-2} \varphi_j \Delta^2 y_{t-i} + \psi' z_t + u_t \qquad (4)$$

which is the auxiliary regression of ADF test on the first differenced data. If the null is not rejected, y_t is at least an I(2) process. Then we test the second differenced data for I(3) against I(2) to verify if higher order of integration exists. Rejecting the null hypothesis will lead us to the second step-to test, testing for I(1) versus I(0).

The results from Dickey-Pantula test are shown in Table 1. Overall, the results allow us to confirm that variables such as $rfsun_t$ and $temp_t$ are I(1) processes. There is also evidence that variables such as ch_{4t}, $n2o_t$, co_{2t}, cfc_{11t} and cfc_{12t} are I(2) variables. Results for $n2o_t$ are not clear. Evidence suggests possible presence of an explosive root.

Now it is of our interest to discriminate I(2) process against explosive root. For that, an F-test proposed by Hasza and Fuller (1979) for double unit roots is applied. As it is two-sided, the F-test has higher power to discriminate against explosive alternatives. The testing procedure is to first apply F-test, if the null of double unit roots is rejected, then the series is either I(0), I(1) or explosive, which can be further tested by ADF test. The F-test is based on the following regression

$$\Delta^2 y_t = \psi' z_t + (\alpha_1 - 1)y_{t-1} + (\alpha_2 - 1)\Delta y_{t-1} + \sum_{k=1}^{p-2} \varphi_j \Delta^2 y_{t-k} + u_t$$

where the method used to select the number of lags is the same as that of the ADF test. Two versions of the F-test are presented. In the first version, we impose two restrictions: $\alpha_1 = 1$, $\alpha_2 = 1$. In the second version, we add two more constraints which are the non-existence of the intercept and the time trend.

The results from the F-test are presented in Table 2. Overall, these results confirm those obtained previously using the Dickey-Pantula procedure. Table 3 also presents a summary of the integration orders of the time series involved, where variable $n2o$ is apparently an explosive process, and therefore we exclude this variable in the following analysis.

4 An I(2) Cointegration Analysis

4.1 Theoretical Issues

We follow the approach suggested by Johansen (1992), where the number of cointegrating vector is chosen based on a representation of I(2) systems. Consider the general VAR model with Gaussian errors in n-dimensions

$$Y_t = \sum_{i=1}^{k} A_i Y_{t-i} + \epsilon_t \tag{5}$$

where $t = 1, 2, ..., T$. Following a similar notation as used in Rahbek et al. (1999), the system (5) can be expressed in the following convenient form

$$\Delta^2 Y_t = \Pi Y_{t-2} - \Gamma \Delta Y_{t-1} + \sum_{i=1}^{k-2} \Psi_i \Delta^2 Y_{t-i} + \mu_0 + \mu_1 t + \epsilon_t \tag{6}$$

where there exists a relation between the parameters $\Gamma, \Pi, \Psi_1, \Psi_2, ..., \Psi_{k-2}$ and the parameters $A_1, A_2, ..., A_k$ which are obtained by identifying the coefficients of the lagged values of Y_t in the two different expressions. Notice that we include an intercept and a deterministic linear trend in (6). Seasonal dummies may be also included.

Define the matrices α and β of dimension $n \times r$ with $r < n$ and $\alpha_\perp$ and $\beta_\perp$ of dimension $n \times (n-r)$ so that $\alpha' \alpha_\perp = 0$ and $\beta' \beta_\perp = 0$. Thus, $\alpha_\perp$ and $\beta_\perp$ are orthogonal complements of α and β, respectively. Similar notation is used in the following to denote orthogonal complements of other matrices. Define the matrices ϕ and η of full ranks and orders $(n-r) \times s$ with $s < (n-r)$. Let $\alpha_1 = \alpha_\perp \phi$, $\beta_1 = \beta_\perp \eta$, $\beta_2 = (\beta, \beta_1)_\perp$ and $\alpha_2 = (\alpha, \alpha_1)_\perp$. Therefore, $(\alpha, \alpha_1, \alpha_2)$ are mutually orthogonal and span $\Re^n$. A similar property is valid for $(\beta, \beta_1, \beta_2)$.

Then, the necessary conditions for Y_t to be an I(2) process are $\Pi = \alpha' \beta$ is of reduced rank r, and that $\alpha'_\perp \Gamma \beta_\perp = \phi \eta'$ is of reduced rank $s < (n-r)$. See Rahbek et al. (1999) regarding further details about restrictions on the deterministic components.

On the other hand, Johansen (1995a, 1995b) has shown that the space spanned by the vector Y_t can be decomposed into r stationary directions β

and $(n-r)$ nonstationary directions $\beta_\perp$. Furthermore, the latter may be decomposed into 2 directions: $\beta_1 = \beta_\perp \eta$ of dimension $p \times s$, and $\beta_2 = (\beta, \beta_1)_\perp$ of dimension $p \times s_2$ where $s + s_2 = n - r$. In the direction of β, the process $\beta' Y_t$ may be made stationary with suitable linear combinations of ΔY_t. In the direction of β_1, the process can be made stationary applying first-order differences. In the direction of β_2, the process can be made stationary only using second-order differences.

A restricted VAR denoted by $H_{r,s}$, is written as

$$\Delta^2 Y_t = \alpha' \beta Y_{t-2} - \Gamma \Delta Y_{t-1} + \sum_{i=1}^{k-2} \Psi_i \Delta^2 Y_{t-i} + \mu_0 + \alpha \beta_0' t + \epsilon_t \qquad (7)$$

where its statistical analysis is performed following the two-step procedure suggested by Johansen (1995a). In the first step the parameters Γ and μ_0 are unrestricted and the reduced rank of Π is addressed with the restriction imposed on μ_1. This model with rank less or equal to r is denoted H_r and it is equivalent to the I(1) model with a restricted linear regressor. In the second step $H_{r,s}$ is analyzed with (α, β, β_0) and r are assumed known. Then, the reduced rank of $\alpha'_\perp \Gamma \beta_\perp$ is addressed with the restrictions imposed on μ_0. In this sense, the models are nested as $H_{r,0} \subset \cdots \subset H_{r,s} \subset \cdots \subset H_{r,n-r} \subset H_r \subset H_n$. Using $Y^*_{t-2} = (Y'_{t-2}, t)'$, $\beta^* = (\beta', \beta'_0)'$, and $\Phi Z_t = \sum_{i=1}^{k-2} \Psi_i \Delta^2 Y_{t-i}$, the model (7) may be written as

$$\Delta^2 Y_t = \alpha' \beta^* Y^*_{t-2} - \Gamma \Delta Y_{t-1} + \Phi Z_t + \mu_0 + \epsilon_t. \qquad (8)$$

Denoting R_{0t}, R_{1t} and R_{2t} as the residuals from regressions of $\Delta^2 Y_t$, ΔY_{t-1} and Y^*_{t-2} against Z_t and a constant, then the maximum likelihood estimator of β^* is found by reduced rank regression of R_{0t} and R_{2t} corrected for R_{1t}. Therefore, the likelihood ratio test $Q(H_r|H_n)$ of $rank(\Pi) \preccurlyeq r$ in $rank(\Pi) \preccurlyeq n$ is given by $Q_r = -2lnQ(H_r|H_n) = -T \sum_{i=r+1}^{n} ln(1 - \widehat{\lambda}_i)$, where $\widehat{\lambda}_i$ $(i = 1, 2, ..., n)$ are the eigenvalues solving the $(n+1)$-dimensional eigenvalue problem.

Following Johansen (1995a), the system is then split into the marginal model for $\alpha'_\perp \Delta^2 Y_t$ containing the reduced restrictions $(\phi \eta')$; and the conditional model for $\alpha(\alpha'\alpha)^{-1} \Delta^2 Y_t$ given $\alpha'_\perp \Delta^2 Y_t$. Interestingly, both systems can be analyzed separately. Model (8) may be transformed into the following form

$$\begin{aligned} \alpha'_\perp \Delta^2 Y_t &= \phi \eta^{*\prime} \begin{pmatrix} \beta_\perp (\beta'_\perp \beta_\perp)^{-1} \Delta Y_{t-1} \\ 1 \end{pmatrix} \\ &\quad - [\alpha'_\perp \Gamma \beta_\perp (\beta'_\perp \beta_\perp)^{-1}] \beta^{*\prime} \Delta Y^*_{t-1} + \alpha'_\perp \Phi_t + \alpha'_\perp \epsilon_t \end{aligned}$$

where $\eta^* = (\eta', \eta_0')'$ and $\Delta Y_{t-1}^* = (\Delta Y_{t-1}, 1)'$. Defining the residuals $R_{\alpha_\perp t}^*, R_{\beta t}^*$ and $R_{\beta_\perp t}^*$ obtained from $\alpha'_\perp \Delta^2 Y_t, \beta^{*\prime} \Delta Y_{t-1}^*$ and $[(\beta_\perp(\beta'_\perp\beta_\perp)^{-1}\Delta Y_{t-1})', 1]'$ corrected for Z_t, the $(n-r+1)$-dimensional eigenvalue problem produces $n-r+1$ eigenvalues denoted by $\widehat{\gamma}_i$. Finally, the likelihood ratio test of $rank$ $(\alpha'_\perp \Gamma \beta_\perp) \preccurlyeq s$ in $rank$ $(\alpha'_\perp \Gamma \beta_\perp) \preccurlyeq n-r$ for know $(\alpha,\ \beta,\ \beta_0)$ is given by $Q_{r,s} = -2lnQ(H_{r,s}|H_{r,n-r}) = -T\sum_{i=s+1}^{n-r} ln(1-\widehat{\gamma}_i)$. Thus, the joint test statistic for the hypothesis $H_{r,s}$ against H_n is given by $S_{r,s} = Q_r + Q_{r,s}$. Asymptotic critical values are tabulated by Johansen (1995a), Paruolo (1996) and Rahbek et al. (1999) according to the different specifications of the deterministic components.

4.2 Empirical Analysis

In the following analysis we consider $n = 6$ with the vector $Y_t = (temp_t,$ $rfsun_t, rfch_{4t}, rfco_{2t}, rfc_{11t}, rfc_{12t})'$. An intercept and a linear time trend are included in the representation of the unconstrained VAR. The six-largest eigenvalues of the companion matrix are $1.00 \pm 0.03i, 0.99 \pm 0.12, 0.84 \pm 0.12i$ reflecting the presence of four unit roots in the system.

Table 4 presents the I(1) and I(2) cointegrating rank analysis described before and the p-values are shown in parenthesis. Observing the row corresponding to $r = 0$, we observe a strong reject of the null hypothesis. The first non-reject, with a p-value of 0.145, is found for $r = 4$, implying that $n - r - s = s_2 = 1$. Thus $s = 1$ and $s_2 = 1$, which indicates the presence of one polynomial cointegrating relationship and one common I(2) trend component in the system. Notice that, in this case, the total number of unit roots is given by $s + 2s_2 = 3$ suggesting the presence of three unit roots.

As suggested by Juselius (1998), a good advice is to compare these results with those obtained from the eigenvalues of the companion matrix. In our case, we observe that both tools offer different results with the eigenvalues suggesting one additional possible unit root which can suggest $s = 2$ and $s_2 = 1$, or $s = 0$ and $s_2 = 2$. On one hand, the results from cointegrating rank analysis suggest $r = 4$ or $r = 5$. The latter is possible if we use the Trace test. But the cointegrating rank analysis detected the first non-reject when $r = 4$. Consequently, we use this result in the following. The fact that $r = 4$ implies that there are two unit roots coming from I(1) components, because $n - r = 2$. If this is the case, then there exists at least one I(2) common trend.

On the other hand, when estimating a cointegrated VAR with $r = 4$, the eigenvalues of the companion matrix suggest five unit roots which seems suggesting that two unit roots are from the imposition of the rank deficiency condition and there are possibly more than one I(2) components. In any case, the evidence for the presence of at least one common I(2) trend is strong.

The presence of at least one I(2) component is due strictly to the four gas-variables $rfch_{4t}, rfco_{2t}, rfc_{11t}, rfc_{12t}$. It is intuitive given the fact that they are I(2) variables according to the univariate analysis performed in the last section. As a confirmatory analysis, we estimate an unrestricted VAR model for the other two variables ($temp_t, rfsun_t$). This time, the I(1) and I(2) cointegrating rank analysis suggested no presence of I(2) components.

Following the approach of Fiess and MacDonald (2001), the goal is to specify some transformation of I(2) variables so that a reduction from an I(2) space to an I(1) space is reached. In other words, the goal is to discover if the common I(2) trends can be expressed as I(1) relationships. We proceed to analyze a VAR only including the four I(2) variables which means that now the vector $Y_t = (rfch_{4t}, rfco_{2t}, rfc_{11t}, rfc_{12t})'$. Using the same deterministic components as before, the five-largest eigenvalues of the companion matrix are $1.00 \pm 0.03i, 0.988 \pm 0.13i, 0.87$, suggesting the presence of four unit roots in the system. Results from the I(1) and I(2) cointegrating rank analysis are presented in Table 5. In this case the first non-reject is found when $r = 2$ and $n - r - s = s_2 = 1$ with a $p - value = 0.237$. These results suggest again the existence of one I(2) component and therefore three unit roots in the system. Estimating a cointegrated VAR with the constraint of $r = 2$, the eigenvalues of the companion matrix are $1.00, 1.00, 0.983, 0.99 \pm 0.07$, suggesting five unit roots and confirming the presence of at least one I(2) component in the system.

Using the four-gas variables, the estimation of a cointegrated VAR with $r = 2$ was performed. Many set of restrictions were tried until we arrive to the identification of the following two cointegrating vectors:

$$\begin{aligned} c_{1t} &= rfc_{11t} - 0.091567 rfc_{12t} + 0.091567 rfch_{4t} - 0.045784 rfco_{2t} \\ c_{2t} &= rfch_{4t} - rfc_{11t} + 0.48865 rfc_{12t} - 0.24433 rfco_{2t} \end{aligned}$$

where a $\chi^2_{(7)} = 4.30$ with a $p - value = 0.74$ indicating that the restrictions cannot be rejected. This p-value also includes a set of exogeneity restrictions. In fact, the variables rfc_{11t}, rfc_{12t} and co_{2t} are found to be weakly exogenous. Application of ADF test to c_{1t} and c_{2t} confirmed that these series are I(1) processes. In other words the linear combinations specified by c_{1t} and c_{2t} reduce the space I(2) to the space I(1). Therefore, in the following, we use a standard I(1) cointegration framework with all I(1) variables. Also notice that first differences of the I(2) variables are I(1) processes and consequently they may enter the I(1) analysis of cointegration.

Now, we consider the following two cases. In the first case, the vector of I(1) series is $Y_t = (temp_t, rfsun, \Delta rfc_{11t}, \Delta rfco_{2t}, c_{2t})'$. In the second case, we have $Y_t = (temp_t, rfsun, \Delta rfc_{11t}, \Delta rfch_{4t}, c_{2t})'$. Notice that both cases excludes the presence of c_{1t} series and they are essentially different according to which I(2) variable is considered in first-differences. Table 7 presents the results from the cointegrating analysis for both cases. In the first case, the eigenvalues of the companion matrix suggest there are two unit roots in the system. In this case, we consider $r = 3$ given that the result of the *Max-test* (adjusted for the sample size) indicating a reject at 10.0% of the null hypothesis of $r = 2$. In the second case, the eigenvalues indicate there are only 2 unit roots in the system. Observing the results of the cointegrating rank analysis, we cannot reject the null hypothesis that there are only two cointegrating vectors ($r = 2$). Tables 6a and 6b present the I(1) and I(2) cointegrating rank analysis for both cases. Notice that the results seem suggesting the presence of I(2) components. However, following Juselius (1998) and observing the eigenvalues of the companion matrix in both cases, the presence of I(2) components is not supported.

From the above analysis, we have three cointegrating vectors for the first case and two cointegrating vectors for the second case. In both cases, no restrictions were imposed on the cointegrating vectors and Figure 2 shows the evolution of the cointegrating vectors, confirming visually that they are stationary.

Now, we proceed to the I(0) analysis using these unrestricted vectors. The estimation is performed by full information maximum likelihood approach with one lag. For the first case, the results (only for the equation of temperature) without imposing any restrictions on the coefficients are presented in Table 8. The bottom panel of the table presents the same results but for the second case. Table 9 presents final results after imposing a set of restrictions regarding the insignificance of some variables[6]. The bottom panel shows the results from the application of diagnostic tests to the equation of temperature. Similar output is presented in Table 10 but for the second case. Both set of results suggest a clear long-term effect of GHGs on GMT. Diagnostic tests indicate that this equation is adequate except for some problems of heteroskedasticity. Figure 3 shows graphical evidence from the estimation of the cointegrated VAR of the two cases for the equation of temperature. The left column presents the results associated with the first case and the second column shows the results from the second case. In each case, the first graph presents the level of the series with their fitted values.

[6] We decide to keep variables with a t-ratio larger or equal to one.

The second graph shows the estimated density of the residuals compared to a Normal density. The last graph presents the ACF of the residuals where we observe the absence of autocorrelation.

Finally, Figure 4 presents graphical evidence for the equation of temperature obtained from recursive estimations for case 1 and case 2 in left and right columns, respectively. The first picture present the 1-step residuals, the second picture shows 1-step Chow tests and the third picture presents the break-point Chow tests. From all pictures, we observe that the residuals of the estimated equation of temperature are inside of the 2 standard error borders. Furthermore, there is no evidence of instability according to the results of the 1-step Chow tests and break-point Chow tests.

5 Conclusions

Do human activities indeed cause global warming? This paper attempts to answer this question by reexamining the time series properties of climate variables. Double unit root testing shows most of the radiative forcing of GHGs are integrated of order two. We then apply an I(1) and I(2) cointegrating rank analysis to identify the presence of I(2) components. After finding a linear combination of I(2) variables that cointegrates to an I(1) process, we proceed with the I(1) cointegrating analysis and we identify two possible cases with different rank specifications. Estimation from the equation for GMT suggests that this variable reacts significantly to the cointegrating vectors. This evidence allow us to conclude that human activities affect GMT variations.

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Table 1. Application of the Dickey and Pantula Test

Variables	Lag	t-statistic	Result
		Variables in First-Differences	
$rfch_{4t}$	2	-1.13	Don't reject
$rfn2o_t^*$	3	-6.73	Reject
$rfco_{2t}$	2	-2.91	Don't reject
rfc_{11t}	3	-2.01	Don't reject
rfc_{12t}	2	-1.08	Don't reject
$rfsun_t$	4	-10.41	Reject
$aerosol_t$	3	-9.39	Reject
$temp_t$	1	-12.89	Reject
		Variables in Levels	
$rfn2o_t^*$	4	1.16	Explosive
$rfsun_t$	4	-3.35	Don't reject (5.0%)
$aerosol_t$	2	-5.17	Reject
$temp_t$	3	-2.45	Don't reject
		Variables in Second Differences	
$rfch_{4t}$	1	-11.74	Reject
$rfco_{2t}$	2	-9.76	Reject
rfc_{11t}	2	-2.43	Reject
rfc_{12t}	4	-1.99	Reject

* A quadratic trend was included for this variable

Table 2. Application of the Hasza and Fuller Test

Variables	Lag	t-statistic	Result
		With two constraints	
$rfch_{4t}$	4	7.13	Don't reject
$n2o_t$	3	21.53	Reject
co_{2t}	2	4.32	Don't reject
cfc_{11t}	3	4.16	Don't reject
cfc_{12t}	1	6.94	Don't reject
$rfsun_t$	4	60.22	Reject
$aerosol_t$	1	105.42	Reject
$temp_t$	2	72.81	Reject
		With four constraints	
$rfch_{4t}$	4	4.51	Don't reject
$rfn2o_t$	3	11.38	Reject
$rfco_{2t}$	2	2.25	Don't reject
rfc_{11t}	3	2.36	Don't reject
rfc_{12t}	1	4.86	Don't reject
$rfsun_t$	4	30.14	Reject
$aerosol_t$	1	52.71	Reject
$temp_t$	2	36.42	Reject

Table 3. Summary of the Testing Results

Variables	Sample Size	Dickey-Pantula	Hasza-Fuller
$rfch_{4t}$	1850-2001	I(2)	I(2)
$rfn2o_t$	1850-2001	explosive	I(0), I(1) or explosive
$rfco_{2t}$	1850-2001	I(2)	I(2)
rfc_{11t}	1930-2001	I(2)	I(2)
rfc_{12t}	1930-2001	I(2)	I(2)
$rfsun_t$	1850-2000	I(1)	I(1)
$aerosol_t$	1850-2000	I(0)	I(0)
$temp_t$	1856-2001	I(1)	I(1)

Table 4. Testing for I(1) and I(2) Cointegrating Ranks;
$Y_t = (temp_t, rfsun, rfch_{4t}, rfco_{2t}, rfc_{11t}, rfc_{12t})'$

r	$S_{r,s}$						Q_r
0	653.44	495.76	417.37	377.66	348.66	328.02	326.09
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1		511.17	363.76	291.57	255.24	227.25	211.47
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2			271.25	201.26	162.94	134.06	129.34
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
3				168.88	101.54	71.97	67.33
				(0.000)	(0.000)	(0.006)	(0.006)
4					68.58	30.62	26.41
					(0.000)	(0.145)	(0.041)
5						21.46	10.05
						(0.030)	(0.126)
$n-r-s=s_2$	6	5	4	3	2	1	

Table 5.Testing for I(1) and I(2) Cointegrating Ranks;
$Y_t = (rfch_{4t}, rfco_{2t}, rfc_{11t}, rfc_{12t})'$

r	$S_{r,s}$				Q_r
0	314.27	245.56	218.53	198.19	196.26
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1		189.56	125.59	99.71	85.60
		(0.000)	(0.000)	(0.000)	(0.000)
2			69.71	28.27	24.48
			(0.000)	(0.237)	(0.072)
3				26.52	7.88
				(0.004)	(0.269)
$n-r-s=s_2$	4	3	2	1	

Table 6a. Testing for I(1) and I(2) Cointegrating Ranks;
Case 1: $Y_t = (temp_t, rfsun, \Delta rfc_{11t}, \Delta rfco_{2t}, c_{2t})'$

r			$S_{r,s}$			Q_r
0	679.10	462.39	319.12	230.10	189.32	177.05
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1		404.10	230.61	148.85	107.41	95.22
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2			288.67	124.05	47.24	35.35
			(0.000)	(0.000)	(0.182	(0.234)
3				97.03	22.81	9.85
				(0.000)	(0.562)	(0.924)
4					12.92	1.97
					(0.323)	(0.956)
$n - r - s = s_2$	5	4	3	2	1	

Table 6b. Testing for I(1) and I(2) Cointegrating Ranks;
Case 2: $Y_t = (temp_t, rfsun, \Delta rfc_{11t}, \Delta rfch_{4t}, c_{2t})'$

r			$S_{r,s}$			Q_r
0	669.32	454.72	308.38	230.87	189.59	171.74
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1		426.03	225.84	149.37	102.80	89.85
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
2			313.91	119.81	47.43	34.13
			(0.000)	(0.000)	(0.177)	(0.287)
3				86.48	19.99	11.68
				(0.000)	(0.745)	(0.830)
4					8.93	2.89
					(0.756)	(0.877)
$n - r - s = s_2$	5	4	3	2	1	

Table 7. I(1) Cointegrating Rank Analysis

Rank	Trace-Statistic (p-value)	Max-Statistic (p-value)
Case 1: $Y_t = (temp_t, rfsun, \Delta rfc_{11t}, \Delta rfco_{2t}, c_{2t})'$		
0	164.58 (0.000)	76.07 (0.000)
1	88.51 (0.000)	55.65 (0.000)
2	32.86 (0.349)	23.71 (0.092)
3	9.16 (0.949)	7.33 (0.868)
4	1.83 (0.965)	1.83 (0.966)
Case 2: $Y_t = (temp_t, rfsun, \Delta rfc_{11t}, \Delta rfch_{4t}, c_{2t})'$		
0	159.64 (0.000)	76.12 (0.000)
1	83.52 (0.000)	51.80 (0.000)
2	31.72 (0.410)	20.86 (0.204)
3	10.86 (0.878)	8.17 (0.802)
4	2.69 (0.897)	2.69 (0.899)

Table 8. FIML Estimations of the Error Correction Model; Equation of Temperature without restrictions

Variables	Coefficients	Standard Errors	p-values
Case 1: $Y_t = (\Delta temp_t, \Delta rfsun_t, \Delta^2 rfc_{11t}, \Delta^2 rfco_{2t}, \Delta c_{2t}, aerosol_t, CIa_{1t}, CIb_{1t}, CIc_{1t})'$			
$\Delta temp_{t-1}$	0.104	0.083	0.212
$\Delta rfsun_{t-1}$	0.209	0.350	0.551
$\Delta^2 rfcf_{11t-1}$	-6.495	8.828	0.463
$\Delta^2 rfco_{2t-1}$	1.518	1.099	0.169
Δc_{2t-1}	-45.382	10.180	0.000
$aerosol_{t-1}$	0.019	0.018	0.303
CIa_{1t-1}	-0.064	0.009	0.000
CIb_{1t-1}	0.005	0.008	0.549
CIc_{1t-1}	-0.015	0.009	0.098
$Intercept$	-0.240	0.053	0.000
Case 2: $Y_t = (\Delta temp_t, \Delta rfsun_t, \Delta^2 rfc_{11t}, \Delta^2 rfch_{4t}, \Delta c_{2t}, aerosol_t, CIa_{2t}, CIb_{2t})'$			
$\Delta temp_{t-1}$	0.034	0.082	0.670
$\Delta rfsun_{t-1}$	0.233	0.356	0.514
$\Delta^2 rfcf_{11t-1}$	-5.450	8.879	0.540
$\Delta^2 rfch_{4t-1}$	4.081	4.789	0.396
Δc_{2t-1}	21.863	6.498	0.001
$aerosol_{t-1}$	0.022	0.019	0.241
CIa_{2t-1}	-0.055	0.009	0.000
CIb_{2t-1}	0.019	0.008	0.026
$Intercept$	-0.149	0.051	0.004

Table 9. FIML Estimations of the Error Correction Model; Equation of Temperature with restrictions,
Case 1: $Y_t =$
$(\Delta temp_t, \Delta rfsun_t, \Delta^2 rfc_{11t}, \Delta^2 rfco_{2t}, \Delta c_{2t}, aerosol_t, CIa_{1t}, CIb_{1t}, CIc_{1t})'$

Variables	Coefficients	Standard Errors	p-values
$\Delta temp_{t-1}$	0.084	0.081	0.298
$\Delta^2 rfco_{2t-1}$	0.812	0.575	0.160
Δc_{2t-1}	-43.805	9.551	0.000
$aerosol_{t-1}$	0.024	0.018	0.172
CIa_{1t-1}	-0.061	0.008	0.000
CIc_{1t-1}	-0.017	0.008	0.034
$Intercept$	-0.246	0.039	0.000
	Diagnostic Tests		
	AR (1-2): $F(2,129) =$	1.63	(0.199)
	Normality: $\chi^2_{(2)} =$	2.56	(0.278)
	ARCH (1): $F(1,133) =$	0.57	(0.451)
	Heteroscedasticity: $F(18,116) =$	1.58	(0.075)
	Heteroscedasticity-X: $F(54,80) =$	1.64	(0.021)
	AIC	-53.06	
	SIC	-52.47	
	HQ	-52.63	

Table 10. FIML Estimations of the Error Correction Model; Equation of Temperature with restrictions,
Case 2:
$Y_t = (\Delta temp_t, \Delta rfsun_t, \Delta^2 rfc_{11t}, \Delta^2 rfch_{4t}, \Delta c_{2t}, aerosol_t, CIa_{2t}, CIb_{2t})'$

Variables	Coefficients	Standard Errors	p-values
Δc_{2t-1}	21.80	5.750	0.000
$aerosol_{t-1}$	0.022	0.018	0.227
CIa_{2t-1}	-0.049	0.006	0.000
CIb_{2t-1}	0.021	0.007	0.004
$Intercept$	-0.101	0.035	0.005
	Diagnostic Tests		
	AR (1-2): $F(2,130) =$	1.66	(0.194)
	Normality: $\chi^2_{(2)} =$	3.98	(0.136)
	ARCH (1): $F(1,133) =$	0.08	(0.774)
	Heteroscedasticity: $F(16,118) =$	2.18	(0.009)
	Heteroscedasticity-X: $F(44,90) =$	1.93	(0.004)
	AIC	-56.68	
	SIC	-56.14	
	HQ	-56.46	

Figure 1. Series in Levels

Figure 2. First Differences of c2 and Cointegrating Vectors from I(1) Analysis (Cases 1: CIa1, CIb1, CIC1 and Case 2: CIa2, CIb2)

Figure 3. Fitted and Real Data, Density and ACF of Residuals; Case 1 (Left Panel) and Case 2 (Right Panel)

Figure 4. 1-step and Chow tests for Error Correction Models; Case 1 (Left Panel) and Case 2 (Right Panel)