

GLOBAL CO₂ EMISSIONS AND GLOBAL TEMPERATURES: ARE THEY RELATED

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ABSTRACT

This paper deals with the analysis of the relationship between CO₂ emissions and temperatures. For this purpose, global CO₂ emissions and four measures of global temperatures (land, land and ocean, northern and southern temperatures) are used. We used techniques based on fractional integration and cointegration. The results indicate first that the orders of integration differ in the two variables. Thus, while emissions are I(1) or I(d) with d higher than 1, temperatures display orders of integration strictly smaller than 1 and thus invalidating the hypothesis of cointegration between the two variables. Due to this, another approach is conducted where we suppose that the emissions are weakly exogenous in relation to the temperatures. The results using this approach show a significantly positive relationship between the two variables with a long memory pattern.

Keywords: Global emissions; global temperatures; long memory; fractional integration

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1. Introduction

Concern about global warming and climate change around the world is increasing. According to Nicholls et al. (1996), Jones and Wigley (2010), Folland et al. (2018), among others, the temperature on the Earth's surface has raised significantly over the last 100 years. This has been caused by industrialization and the effect of burning and emissions of fossil fuel, greenhouse gas concentration that affects the atmosphere (Anderegg et al. 2010; Beckage et al. 2018; etc.), but also by the innate variability of the climate system (e.g. solar irradiance) or by the combination of the two.

The most noticeable aspect is the strong correspondence between temperature and the concentration of carbon dioxide in the atmosphere (see McMillan and Wohar, 2013; Zickfeld et al., 2012; Zickfeld et al., 2016). According to the National Oceanic and Atmospheric Administration (NOAA), carbon dioxide concentration and temperatures have the same behavior and they move in a similar way. This is also supported by authors such as Laat and Maurellis (2004), Hansen et al. (2010); Cahill et al., (2015) and Sanz-Pérez, et al. (2016).

It is also true that the world has experienced changes in weather patterns. These changing patterns have provided a foundation to those who argue that the increase in CO₂ emissions has increased the average temperatures. Thus, in recent years, there has been a growing interest in investigating the stochastic processes and trends in the global temperatures on the one hand (see, e.g., Bloomfield, 1992; Bloomfield and Nychka, 1992; Galbraith and Green, 1992; Woodward and Gray, 1993, 1995; Koenker and Schorfheide, 1994; Zhang and Basher, 1999; Harvey and Mills, 2001; Gil-Alana, 2003; Mills, 2006, 2010; Gay-García et al., 2009; Hendry and Pretis, 2013; Kauffmann et al., 2006, 2010, 2013; Estrada et al., 2013; Chang et al., 2016, etc.), and the emissions on the other hand. Aldy (2006) and Lee and Chang (2009) show the convergence of the

CO₂ emissions series of both industrialized and developing countries. Ezcurra (2007), Panopoulou and Pantelidis (2009), Chang and Lee (2008), Romero-Ávila (2008), Lee et al. (2008), Yavuz and Yilanci (2013), Ahmed et al. (2016) are among the few papers that have investigated the stationarity properties of the CO₂ emissions. Most of this literature, however, tends to focus on the two variables separately, i.e., temperatures and CO₂, and little research has been dedicated to the analysis of the relationship between the two variables.

The existing literature in recent years is based on developing tests to analyze trend behavior. Fomby and Vogelsang (2003) investigated general forms of trending patterns using autocorrelation in the errors of seven global temperature series to detect if the errors are stationary or have a unit root, finding strong evidence of positive deterministic trends. On the other hand, Vogelsang and Franses (2005) employed a regression model to examine global, northern and southern hemispheres temperatures and concluded that there has been a significant worldwide temperature increase. Other authors have claimed the existence of memory or persistence across different regimes in the climate system. Gil-Alana (2003) analyzed Central England Temperatures (CET) using fractional integration techniques to conclude that the increase in the temperatures is about 0.23 °C per 100 years in recent history. Subsequent work by the same author (Gil-Alana, 2005, 2008a,b) used similar techniques in the analysis of global temperatures allowing for potential breaks in the data. Other authors including Eichner et al. (2003), Mills (2007), Lennartz and Bunde (2009), Bunde et al. (2014), Yuan et al. (2015), Ludescher et al. (2016), Massah and Kantz (2016), Bunde (2017) among others also found persistence and evidence of long memory in the temperatures. In the context of CO₂ emissions, authors such as Sun and Wang (1996), Slottje et al. (2001), Nourry (2009), Christidou et al. (2013) Tiwari et al. (2016), Gil-Alana and Solarin (2018) and

Gil-Alana and Trani (2018) to name just a few have examined the stationarity of the emissions. Among the few papers relating temperatures and emissions, McMillan and Wohar (2013) investigated jointly and individually the two variables using unit root tests and others autorregression models, concluding that CO₂ has a weak relationship with temperature, not finding evidence of a trending pattern. Zhang et al. (2019), using a multilayer and multivariable network method, analyzed the dynamics of the upper air on the temporal variability of surface air pollution for the case of China and United States, finding that the association between the two variables was related to the dynamics of planetary Rossby waves that affect air pollution fluctuation through the development of cyclone and anticyclone systems and further affect the local stability of the air and the winds. Finally, Ying et al. (2020) carried out their research assuming that the CO₂ concentration and its spatial distribution, detected by the various satellites, is uneven. To do so, they used a multilayer climate network approach to identify their relations using satellite data. Their findings showed that the probability density function of degrees, weighted degrees, and link lengths follows power-law distributions.

This research paper considers global annual temperatures (land temperatures, land and ocean temperatures and Northern and Southern hemispheres temperatures) and global annual CO₂ emissions¹ from 1880 to 2015. It extends the above mentioned literature with advanced methodologies based on fractional integration to analyze the

¹ Watson and Noble (2002) argued that each year 120 gigatons (Gt) carbon are exchanged between the atmosphere and terrestrial ecosystems and 90 Gt between the atmosphere and the oceans. 6Gt were related to fossil fuel burning, and half of this amount was observed as an increase of the atmospheric CO₂ concentration. On the other hand, and according to Intergovernmental Panel for Climate Change (2007) the oceans and terrestrial system showed a net uptake of carbon.

Knowing that the air-CO₂ provides a tool to quantify the contribution of different components to ecosystem exchange and thanks to the contribution done by Ghosh and Brand (2003) in their study of contemporary isotopic change of natural compartments, we can deduct that the amount of CO₂ we put into the atmosphere could be a causality fact with the amount of CO₂ that remains in the atmosphere. Also, following Ghosh and Brand (2003), from the point of view of the carbon atoms, carbon 12 has 6 neutrons, carbon 13 has 7 neutrons. If plants have a lower C13/C12 ratio that in the atmosphere and the CO₂ comes from fossil fuels, the ratio should be falling, and this is what is occurring. So, the trend of atmospheric CO₂ correlates with the trend in global emissions. For this reason, we use CO₂ emissions instead of CO₂ concentration.

properties of the series (time trends, persistence and seasonality), which have not been jointly studied so far in this context. **In fact, this is one of the contributions of this work, which is methodological, using techniques that have not been used so far and that employ fractional degrees of differentiation unlike the classical methods and that are based exclusively on integer orders of integration, i.e., stationary I(0) or nonstationary I(1) processes.**

The paper is organized as follows: Section 2 briefly describes the techniques used in the paper, while Section 3 presents the dataset and Section 4 contains the empirical results. Finally, Section 5 concludes the paper.

2. Methodology

For the analysis of the individual series we use techniques based on long memory and fractional integration. For this purpose we define an integrated process of order 0 or I(0) as a covariance (or second order) stationary process with the infinite sum of the autocovariances assumed to be finite. There exists an alternatively definition based on the frequency domain, which says that an I(0) process is a process with a spectral density function that is positive and finite at the zero frequency. These two are very broad definitions that include not only the white noise model but also weakly autocorrelated structures such as the one produced by the stationary and invertible AutoRegressive Moving Average (ARMA) type of models. On the other extreme, we can have nonstationary processes, with a unit root and also named integrated of order 1, i.e., I(1), which, in its simplest form, is the random walk model of the form:

$$(1 - B)x_t = u_t, \quad t = 1, 2, \dots, \quad (1)$$

where B is the backshift operator ($Bx_t = x_{t-1}$) and u_t is white noise. Note that if u_t is an ARMA(p, q) process in (1), x_t is then an ARIMA(p, 1, q) process. However, the

stationary I(0) and the nonstationary I(1) cases are both particular cases within a more flexible type of model known as fractionally integrated or I(d) where d can be any real value. Thus, we may consider a model of the form:

$$(1 - B)^d x_t = u_t, \quad t = 1, 2, \dots, \quad (2)$$

where u_t is I(0) and d can be 0, a value between 0 and 1, 1, or even above 1.¹

Processes such as (2) with $d > 0$ belong to a broader category named long memory, which is characterized because the infinite sum of the autocorrelation is infinite, or, alternatively, in the frequency domain, because the spectral density function has a pole or singularity at the smallest, i.e., zero, frequency. They were originally proposed by Granger (1980, 1981), Granger and Joyeux (1980) and Hosking (1981), based on the observation that many aggregated series presented an extremely large value in the estimated spectrum at the smallest frequency, consistent with first differentiation, but once the series were differenced, the estimated spectrum displayed a value close to zero at the zero frequency, which was a clear indication of overdifferentiation. The I(d) models with fractional values of d became very popular in the late nineties throughout the works of authors such as Baillie (1996), Gil-Alana and Robinson (1997), Silverberg and Verspagen (1999) and others, and they have been widely employed in the analysis of global and local temperatures and also in the analysis of CO₂ emissions and other contaminants.

In this paper we estimate the differencing parameter d using a method that uses the Whittle function in the frequency domain as proposed in Dahlhaus (1989), and we implement it through the tests of Robinson (1994), which is very convenient in the context of nonstationary data as those used in this work. Note that the estimation of d is crucial. Thus, for example, x_t is covariance stationary if d is smaller than 0.5. However,

¹ See, Gil-Alana and Hualde (2009) for a review of these models and its applications in time series.

as long as d departs from 0.5 it becomes more nonstationary in the sense that the variance of the partial sums increases with d . Also, if d is smaller than 1, shocks will have a transitory nature and their effects will disappear by themselves in the long run, contrary to what happens if $d \geq 1$ where shocks are not mean reverting and persist forever. Thus, d can be viewed as an indicator of the degree of persistence, the higher its value is, the higher the degree of persistence is in the data.

The multivariate representation of fractional integration is fractional cointegration, initially examined by Peter Robinson and his coauthors (Robinson and Yajima, 2002, Robinson and Marinucci, 2003; Robinson and Hualde, 2003; Hualde and Robinson, 2007; etc.) and later extended to the fractional CVAR (FCVAR) model by Johansen and Nielsen (2010, 2012) and others. However, in a bivariate context, as is the case in this paper, a necessary condition for cointegration is that the two individual series must display the same degree of integration, and this condition is not satisfied in the empirical application carried in Section 5. Therefore, as an alternative approach in this multivariate setting, we employ a version of the tests of Robinson (1994) which uses a regression model where the regressor (CO₂ emissions) is taken as weakly exogenous, and the regression errors are supposed to be $I(d)$ where d can be potentially fractional.²

4. Data

The data examined in this paper are the global annual temperature anomalies computed using data from meteorological stations; global annual temperature anomalies computed from land and ocean; and global annual temperature anomalies for the northern and southern hemispheres computed using land and ocean data.³ We also use data of the

² This methodology has been used for example in Gil-Alana and Henry (2003) and Gil-Alana et al. (2008).

³ <https://cdiac.ess-dive.lbl.gov/trends/temp/hansen/data.html>

global CO₂ emissions originated by fossil fuel burning.⁴ The dataset was obtained from the Carbon Dioxide Information Analysis Center (CDIAC) that is the U.S. Department of Energy's (DOE) Environmental System Science Data Infrastructure for a Virtual Ecosystem.

[Insert Figure 1 here]

Figure 1 plots the original data of the global fossil fuel CO₂ emissions and the four annual anomalies in the temperature series mentioned above. We observe an increasing trend in the analyzed period from 1880 to 2015.

5. Results

We start this section by presenting the univariate results for each of the series under investigation, and the first thing we do is to examine the order of integration of each series from a fractional viewpoint. In order to allow for potential linear trends, and following [Bhargava \(1986\)](#), [Schmidt and Phillips \(1992\)](#) and others on the parameterization of unit root models, we consider the following specification,

$$y_t = \beta_0 + \beta_1 t + x_t, \quad (1 - B)^{d_o} x_t = u_t, \quad t = 1, 2, \dots, \quad (3)$$

where y_t refers to each of the individual series, i.e., CO₂ emissions and its logged values, and each of the four temperature series; β_0 and β_1 are the coefficients referring respectively to an intercept and a linear time trend, and d is the potentially fractional differencing parameter.

We estimate the differencing parameter d along with the remaining coefficients in (3) under three different set-ups: i) with no deterministic components, i.e., imposing $\beta_0 = \beta_1 = 0$ in (3); with a constant/intercept, i.e., $\beta_1 = 0$; and with a linear time trend, i.e., β_0 and β_1 both freely estimated from the data, and we report in bold in the tables the

⁴ https://cdiac.ess-dive.lbl.gov/trends/emis/tre_glob_2014.html

relevant cases for each series according to the corresponding t-values of these deterministic terms.

In Table 1 we assume that u_t in (3) is a white noise process, so no autocorrelation is permitted. The first thing we observe is that the time trend coefficient is required in all series, though the estimated values of d are very different in the two variables. Thus, for the global CO₂ emissions, we see in Table 2 that the estimated values of d are 1.30 and 0.97 respectively for the unlogged and logged emissions, and the I(1) hypothesis cannot be rejected for the latter case. However, for the global temperatures, the values are much smaller ranging between 0.48 (land temperatures) and 0.60 (land + ocean temperatures), and a mean-reverting long memory pattern (i.e., $0 < d < 1$) is found in the four series, which is consistent with the results obtained in other studies with the same or similar data (see Gil-Alana 2003, 2005 and 2008a,b).

[Insert Tables 1 and 2 about here]

In Tables 3 and 4 we allow for autocorrelation in the error term. However, instead of imposing a particular ARMA-type model we use a non-parametric approach developed by Bloomfield (1973) which accommodates extremely well in the context of the methods used in this paper and based on Robinson's (1994) tests. Using this approach, we observe that the time trend coefficients are once more statistically significantly positive (Table 4) in all cases, and the orders of integration, though smaller than in the previous case, qualitatively are very similar to those reported for the case of uncorrelated errors. Thus, as a conclusion of this univariate work, we can say that the order of integration is equal to or higher than 1 for the emissions, and strictly smaller than 1 for the temperatures. Thus, our results indicate that the two variables differ in relation with their orders of integration and this is a serious caveat in the sense that it invalidates any analysis of cointegration between the two variables. Note that a

necessary condition for cointegration in a bivariate case is that the two individual series must display the same degree of integration, and this is clearly not satisfied in our case.

Due to this empirical feature in the data, we have to think of an alternative approach and the one that we propose in this work is to assume that the actual and past values of emissions (in logs) are weakly exogenous in relation to the temperatures. For this purpose, we use again the tests of Robinson (1994) since they are specified in a way that allows us to consider the following model,

$$y_t = \beta^T z_t + x_t, \quad (1 - B)^d x_t = u_t, \quad (1 - \varphi Bz^{12})x_t = \varepsilon_t, \quad (4)$$

where z_t is a $(k \times 1)$ vector of weakly exogenous (or deterministic) regressors. In our case, we choose $z_t = (1, \log EM_{t-k})^T$ where EM refers to CO₂ emissions, for $k = 0, 1, 2, 3, 4$ and 5 ; thus, $\beta = (\beta_0, \beta_1)^T$ and φ is the seasonal (monthly) AR coefficient. The results in terms of the estimated coefficients are reported across Tables 5 – 8 for the four temperature series.

[Insert Tables 5 – 8 about here]

Several features are observed in these tables. First, the slope coefficient is statistically significantly positive in all cases, implying a positive relationship between global CO₂ emissions and global temperatures, and the highest coefficients correspond in all cases to the regressions with land temperatures, following by land and ocean temperatures. For the hemispheres, the values are smaller, being substantially higher in case of the northern temperatures. We do not observe any significant pattern in connection with the lags (k). With regard to d , all values once more suggest fractional integration and a long memory pattern, with d constrained in all cases between 0 and 1. This value is about 0.66 for the southern hemisphere temperatures; slightly higher for the land and ocean temperatures; and much smaller for northern hemisphere and land temperatures.

6. Conclusions

In this paper we have related global CO₂ emissions with the global temperatures by using a long memory model. We used this approach based on the overwhelming evidence supporting the existence of this feature in the data.

We start by conducting the univariate analysis of each series, which are global CO₂ emissions and four temperature series corresponding to land, land and ocean, northern and southern temperature anomalies. The univariate results indicate that the CO₂ emissions are not mean reverting with the estimated value of d (the differencing parameter) being equal to or higher than 1 in all cases. This implies that the series is highly persistent with shocks having permanent effects on the series. For the temperatures, the estimates of the differencing parameters are much smaller, ranging in the interval $(0, 1)$ and thus supporting long memory and mean reversion behavior. Thus, shocks here will be transitory though with long lasting effects. As a consequence of this different pattern in the behavior of the two variables, we impose the assumption that the emissions are (weakly) exogenous, and including this feature in a long memory regression model, the results indicate that the emissions produce a significant positive effect in the temperatures, which is consistent with the works of McMillan and Wohar (2013), Zickfeld et al. (2012), Zickfeld et al. (2016), and others, and at the same time displaying a significant degree of persistent with shocks having long lasting effects. Thus, a shock in the emissions affecting the temperatures will be persistent though transitory and disappearing in the very long run.

This work could be extended in several directions. Thus, for example, CO₂ concentration could have been taken into account instead of CO₂ emissions when looking at a long run relationship between pollution and temperatures. Also, the

analysis could be conducted with data based on different locations to check if the same conclusions hold with specific-located data. Other approaches allowing, for instance, for non-linear deterministic or even stochastic terms can also be explored in the analysis of these and other data. Future work will also examine the relationship of the temperatures with other contaminants.

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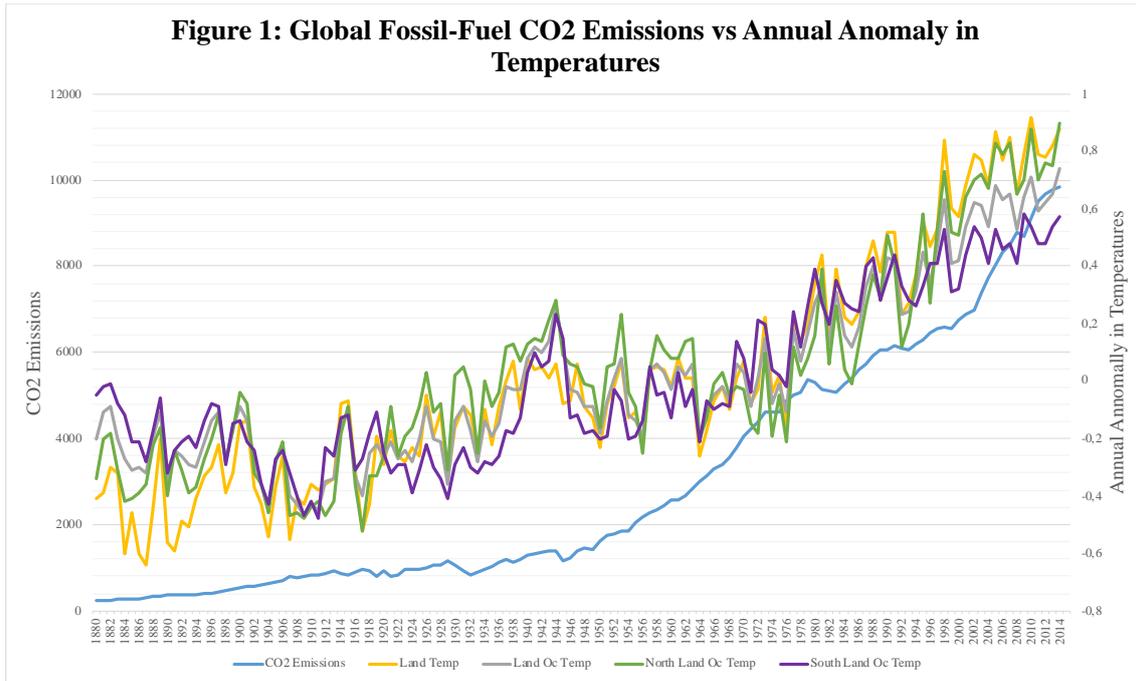


Table 1: Testing the integration order under the hypothesis of no autocorrelation

| Series | No terms | An intercept | A linear time trend |
|-------------------------------|-------------------|-------------------|--------------------------|
| CO ₂ Emissions | 1.26 (1.19, 1.38) | 1.27 (1.19, 1.39) | 1.30 (1.22, 1.41) |
| Log CO ₂ emissions | 0.97 (0.87, 1.11) | 0.96 (0.86, 1.12) | 0.97 (0.87, 1.11) |
| Land temp. | 0.63 (0.57, 0.72) | 0.59 (0.53, 0.66) | 0.48 (0.39, 0.59) |
| Land ocean temp. | 0.67 (0.60, 0.76) | 0.65 (0.58, 0.75) | 0.60 (0.50, 0.72) |
| Northern hem. temp. | 0.62 (0.55, 0.71) | 0.59 (0.53, 0.69) | 0.54 (0.45, 0.66) |
| Southern hem. temp. | 0.69 (0.62, 0.79) | 0.68 (0.61, 0.78) | 0.64 (0.55, 0.76) |

In bold the significant cases according to the deterministic terms. In parenthesis the 95% confidence bands for the values of d.

Table 2: Estimated coefficients under the hypothesis of no autocorrelation

| Series | d | Intercept | A linear time trend |
|-------------------------------|-------------------|-----------------|---------------------|
| CO ₂ Emissions | 1.30 (1.22, 1.41) | 196.390 (2.16) | 64.729 (2.15) |
| Log CO ₂ emissions | 0.97 (0.87, 1.11) | 5.437 (108.17) | 0.0278 (7.35) |
| Land temp. | 0.48 (0.39, 0.59) | -0.5145 (-6.04) | 0.0090 (7.29) |
| Land ocean temp. | 0.60 (0.50, 0.72) | -0.2571 (-3.13) | 0.0062 (4.08) |
| Northern hem. temp. | 0.54 (0.45, 0.66) | -0.3803 (-3.83) | 0.0077 (4.80) |
| Southern hem. temp. | 0.64 (0.55, 0.76) | -0.1249 (-1.50) | 0.0046 (2.65) |

The values in parenthesis in the 3rd and 4th columns are the associated t-values.

Table 3: Testing the integration order under the hypothesis of weak autocorrelation

| Series | No terms | An intercept | A linear time trend |
|-------------------------------|-------------------|-------------------|--------------------------|
| CO ₂ Emissions | 1.24 (1.13, 1.40) | 1.23 (1.12, 1.39) | 1.27 (1.15, 1.44) |
| Log CO ₂ emissions | 0.93 (0.76, 1.18) | 0.87 (0.76, 1.14) | 0.89 (0.74, 1.11) |
| Land temp. | 0.69 (0.59, 0.81) | 0.63 (0.53, 0.73) | 0.48 (0.37, 0.64) |
| Land ocean temp. | 0.68 (0.59, 0.81) | 0.65 (0.54, 0.77) | 0.55 (0.41, 0.72) |
| Northern hem. temp. | 0.66 (0.56, 0.80) | 0.62 (0.53, 0.75) | 0.56 (0.41, 0.71) |
| Southern hem. temp. | 0.68 (0.59, 0.84) | 0.68 (0.58, 0.81) | 0.59 (0.42, 0.79) |

In bold the significant cases according to the deterministic terms. In parenthesis the 95% confidence bands for the values of d.

Table 4: Estimated coefficients under the hypothesis of weak autocorrelation

| Series | d | Intercept | A linear time trend |
|-------------------------------|-------------------|-----------------|---------------------|
| CO ₂ Emissions | 1.27 (1.15, 1.44) | 194.564 (2.14) | 66.743 (2.51) |
| Log CO ₂ emissions | 0.89 (0.74, 1.11) | 5.4413 (109.38) | 0.0278 (10.53) |
| Land temp. | 0.48 (0.37, 0.64) | -0.5145 (-6.05) | 0.0090 (7.29) |
| Land ocean temp. | 0.55 (0.41, 0.72) | -0.2759 (-3.60) | 0.0062 (4.92) |
| Northern hem. temp. | 0.56 (0.41, 0.71) | -0.3752 (-3.67) | 0.0077 (4.47) |
| Southern hem. temp. | 0.59 (0.42, 0.79) | -0.1486 (-1.90) | 0.0046 (3.26) |

The values in parenthesis in the 3rd and 4th columns are the associated t-values.

**Table 5: Estimated coefficients in a regression with I(d) errors
(Land temperatures / Log emissions)**

| Tland / Lem | d (95% conf. band) | β_0 (t-value) | β_1 (t-value) |
|-------------|--------------------|---------------------|---------------------|
| k = 0 | 0.53 (0.45, 0.64) | -1.9057 (-5.56) | 0.2644 (5.03) |
| k = 1 | 0.54 (0.46, 0.65) | -2.1185 (-6.15) | 0.3001 (5.63) |
| k = 2 | 0.52 (0.44, 0.64) | -1.9956 (-5.97) | 0.2821 (5.53) |
| k = 3 | 0.52 (0.44, 0.64) | -2.1075 (-6.30) | 0.2965 (5.80) |
| k = 4 | 0.52 (0.43, 0.63) | -2.2566 (-6.72) | 0.3099 (6.03) |
| k = 5 | 0.52 (0.44, 0.64) | -2.1320 (-6.28) | 0.2960 (5.69) |

**Table 6: Estimated coefficients in a regression with I(d) errors
(Land-Ocean temperatures / Log emissions)**

| Tland / Lem | d (95% conf. band) | β_0 (t-value) | β_1 (t-value) |
|-------------|--------------------|---------------------|---------------------|
| k = 0 | 0.64 (0.56, 0.75) | -1.0457 (-2.85) | 0.1519 (2.51) |
| k = 1 | 0.65 (0.56, 0.77) | -1.3402 (-3.61) | 0.2090 (3.38) |
| k = 2 | 0.63 (0.54, 0.74) | -1.1981 (-3.35) | 0.1825 (3.11) |
| k = 3 | 0.62 (0.53, 0.74) | -1.3361 (-3.85) | 0.1956 (3.45) |
| k = 4 | 0.61 (0.53, 0.73) | -1.2640 (-3.67) | 0.1779 (3.18) |
| k = 5 | 0.62 (0.53, 0.74) | -1.3756 (-3.88) | 0.1946 (3.35) |

**Table 7: Estimated coefficients in a regression with I(d) errors
(Northern Land-Ocean temperatures / Log emissions)**

| NTland / Lem | d (95% conf. band) | β_0 (t-value) | β_1 (t-value) |
|--------------|--------------------|---------------------|---------------------|
| k = 0 | 0.59 (0.50, 0.69) | -1.4224 (-3.38) | 0.2003 (2.98) |
| k = 1 | 0.58 (0.50, 0.69) | -1.3925 (-3.40) | 0.1949 (3.00) |
| k = 2 | 0.58 (0.50, 0.69) | -1.3844 (-3.36) | 0.1935 (2.95) |
| k = 3 | 0.58 (0.49, 0.69) | -1.3660 (-3.29) | 0.1904 (2.88) |
| k = 4 | 0.58 (0.50, 0.70) | -1.3929 (-3.33) | 0.1949 (2.92) |
| k = 5 | 0.58 (0.49, 0.69) | -1.3273 (-3.17) | 0.1837 (2.75) |

**Table 8: Estimated coefficients in a regression with I(d) errors
(Southern Land-Oceanic temperatures / Log emissions)**

| STland / Lem | d (95% conf. band) | β_0 (t-value) | β_1 (t-value) |
|--------------|--------------------|---------------------|---------------------|
| k = 0 | 0.66 (0.56, 0.78) | -0.7252 (-1.95) | 0.1145 (1.84) |
| k = 1 | 0.66 (0.57, 0.78) | -0.7080 (-1.90) | 0.1115 (1.79) |
| k = 2 | 0.66 (0.57, 0.78) | -0.6871 (-1.83) | 0.1078 (1.72) |
| k = 3 | 0.66 (0.57, 0.78) | -0.6869 (-1.81) | 0.1077 (1.70) |
| k = 4 | 0.66 (0.57, 0.78) | -0.7020 (-1.84) | 0.1104 (1.73) |
| k = 5 | 0.66 (0.57, 0.78) | -0.6972 (-1.81) | 0.1095 (1.70) |