PERSISTENCE, MEAN-REVERSION AND NON-LINEARITIES IN CO_2 EMISSIONS: EVIDENCE FROM THE BRICS AND THE G7 COUNTRIES

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Abstract

This study examines the time series behaviour of CO_2 emissions within a long memory approach with non-linear trends and structural breaks using long span of data for the BRICS and the G7 countries. The main results show significant differences both in the degree of integration and non-linearities among the analyzed countries. Thus, the CO_2 emissions series display, in most of the cases, orders of integration equal to or higher than 1, implying permanent effects of shocks in CO_2 emissions. The only exceptions are Germany, the US and the UK, where shocks will have transitory effects. With respect to the non-linearities, more evidence of non-linear behaviour is obtained in the G7 countries, especially in the cases of the US, the UK, Germany and France. Partial evidence is also found in Canada and India. The significantly different results obtained for emerging and developed economies have important policy implications.

JEL classification: C22, C32, Q28, Q50

Keywords: CO_2 emission, long memory, non-linear trends

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1. Introduction

According to the "Trends in Global CO_2 emissions" 2014 report from the *European Commission*, the top emitting regions in 2014 of the total global CO_2 emissions were China (10.3 billion tons), US (5.3 billion tons), the European Union (3.7 billion tons), India (1.8 billion tons), the Russian Federation (1.7 billion tons) and Japan (1.4 billion tons), with a 29%, 15%, 11%, 6%, 5% and a 4% of the total emissions, respectively. However, considering the cumulative CO_2 emissions from 1900, these figures changes and the top emitting countries are US (with 314,772 million metric tons of carbon dioxide), European Union (with 287,636) and Russia and China (with 89,688 and 89,243), while the cumulative emissions for Japan and India are 44,502 and 25,054 million (see *World Resources Institute*). All these data suggest that the CO_2 emissions of the BRICS (Brazil, Russia, India, China and South Africa) countries represent a 37% of the total emissions in 2014 and a 20% of the cumulative emissions from 1900. In contrast, the CO_2 emissions of the G7 (US, UK, Japan, Canada, Germany, France and Italy) account for a third of global carbon emissions in 2014, and a 54% of the cumulative emissions from 1900. The long-run effect of gas emissions on climate change and the heterogeneous gas emission patterns of the BRICS and G7 countries, which is very much related to their degree of development, justifies a long-run analysis of the dynamics of the global carbon dioxide variable across these different countries. Furthermore, total carbon emissions among the BRICS and G7 countries account for a 70% of the total emissions and three quarters of the cumulative carbon emissions, which justifies the inclusion of these 12 countries in the analysis.

The time series properties of the CO_2 emissions variables will shed some light on the degree of stationarity of this variable in each of the countries and in different subsamples. For instance, if this variable is stationary, shocks have transitory effects, and policy intervention should not have to be very urgent given the transitory effects of the shocks on this variable. By contrast, if the CO_2emissions are non-stationary, strong policy interventions will be required since the shocks will have permanent effects. The relevant energy and environmental policy implications of the time series properties of this variable explains the ample literature on the econometric modelling of this variable using alternative unit root tests (see, for example, Strazicich and List, 2003; Lanne and Liski, 2004; McKitrick and Strazicich, 2005; Nguyen, 2005; Aldy, 2006; Ezcurra, 2007; Barasi et al., 2008; Romero-Avila, 2008; or Panopoulou and Pantelidis, 2009, among others). Despite the vast literature on the integration order of this variable, the results are not yet conclusive.

The long-run CO_2 emissions data reveals that global CO_2 emissions are now 150 times higher than they were at 1850, the beginning of our sample period. Furthermore, the observed increased in this variable during these 150 years has not been constant nor linear, as neither has been the evolution of its main drivers: population growth, economic development and energy use. By contrast, several episodes may have caused several disruptions, and thus, non-linearities in the temporal evolution of this variable: the industrialization processes, the Great Depression and other economic crisis, the emerging of Asian countries, different energy and oil shocks, some climate change regulatory initiatives, etc. The non-linear behavior of this variable has been mostly modeled in the literature by the inclusion of structural breaks (see, for example, Lanne and Liski, 2004; McKitrick and Strazicich, 2005; or Lee and Chang, 2009, among others), while only a few attempts have been made modelling non-linearities (see, for example, Musolesi and Mazzanti, 2014, or Gil-Alana et al., 2015, among the few). In this paper, we use both the structural breaks, along with the non-linear modelling, to analyze the time series properties of the CO_2 emissions series. The analysis of non-linearities in the CO_2 emissions series, together with the structural breaks, will have important policy implications, since they will help us understand the heterogeneous historical evolution of each of the series, the differences among the analyzed countries and the potential effects of the above changes on CO_2 series.

The contribution of this paper is two-folded. First, we provide evidence of the long memory properties of the carbon dioxide emissions for a long span of data allowing for non-linear deterministic trends in the form of Chebyshev polynomials in time. Second, including in the analysis the BRICS emerging economies (Brazil, Russia, India, China and South Africa) together with the G7 advanced economies (the US, the UK, Japan, France, Italy, Germany and Canada) will allow us to compare time series properties of this variable among countries with different degree of development.

The remainder of the paper is structured as follows: Section 2 revises the literature on CO_2 emissions and mean reversion. Section 3 describes the methodology and justifies its application in the context of CO_2 emission variables. Section 4 presents the data and the main empirical results, while Section 5 contains some concluding comments and policy implications.

2. Literature review

Modeling the dynamic behavior of CO_2 emission series has become a relevant research area based on the relevance of this variable on global warming and climate change. Thus, a growing literature has examined the stationarity of CO_2 series using different time series techniques, different sample of countries and time periods. For example, Heil and Selden (1999) test for unit roots in these series for a group of 135 countries over the period 1950-1992, finding evidence of stationarity in only 20 of the 135 analyzed countries. Chistidou et al (2013) examine the stationarity of carbon dioxide emissions per capita for a set of 36 countries covering the period 1870-2006 and by grouping the countries by their geographical proximity. They find strong evidence that per capita carbon dioxide emissions are stationary. Lanne and Liski (2004) analyze the stationary properties of carbon dioxide emissions for 16 OECD countries over the period 1870-1998, allowing for structural breaks, finding strong evidence of structural breaks occurring in the 1970s, coinciding with the oil price shocks. McKitrick and Strazicich (2005) test for stationarity of this variable in 121 countries for the period 1950-2000 allowing for structural breaks, obtaining evidence against the unit root hypothesis in most of the countries, together with significant evidence of structural breaks. Ordás and Grether (2011) investigate the stationarity of per capita CO_2 emissions with a panel of 166 countries covering the period 1960-2012 by means of analyzing the evolution of spatial distributions over time. Barassi et al. (2011) use a long memory approach to examine whether per capita carbon dioxide emissions are fractionally integrated.

Although the inclusion of structural breaks in the univariate analysis of CO_2 series is common in the literature, only a few papers include non-linear deterministic trends when calculating the fractional integration order of the series (Gil-Alana et al., 2015). These authors analyze the issue of persistence in carbon emission allowance spot prices using daily data for the period 2007-2014 accounting for structural breaks and nonlinearities in the data. Although the authors do not find evidence of non-linearities in their series in this period, we apply the same methodology for the CO_2 emission series in the BRICS and G7 countries for a much longer time series data, believing that the inclusion of non-linearities in the model will be a significant contribution of the paper to the literature, since it will help us to analyze the effect of numerous economic, energy and environmental disruptions on the CO_2 series occurred over the last one hundred and fifty years.

This paper examines the long memory properties of the carbon dioxide emissions for Brazil, Russia, India, China and South Africa (BRICS) and for the US, the UK, France, Italy, Germany, Japan and Canada (G7 countries) using a long span of data and allowing for non-linear deterministic trends in the form of Chebyshev polinomials. The different results obtained on the order of integration of the series for each of the countries and on the existence of significant non-linearities in each of the series will have different policy implications for each of the countries examined.

3. Methodology

In this paper we use fractional integration (or I(d)) to describe the behavior of the CO_2 emissions. This is a very general specification that allows us to consider the stationary I(0) and the nonstationary I(1) as particular cases of interest when d = 0 and d = 1, respectively.

Given a covariance stationary process $\{u_t,\ t = 0, \pm 1, \ldots\}$, we say that it is integrated of order 0 (and denoted by $u_t \approx I(0)$) if it has a spectral density function that is positive and finite at the zero frequency. Having said this, a process is integrated of order d, (and denoted as $x_t \approx I(d)$) if it can be represented as

$$(1 - L)^d x_t = u_t, \qquad t = 0, \pm 1, \ldots, \tag{1}$$

with $x_t = 0$ for $t \leq 0$, and $d > 0$, where L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is $I(0)$. By allowing *d* to be fractional, we permit a much richer degree of flexibility in the dynamic specification of the series, not achieved when using the classical approaches based on integer differentiation, i.e., d = 0 and d = 1. Note that the left hand side of equation (1) can be expressed for all real d as:

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \frac{d(d-1)(d-2)}{6} L^3 + \dots$$

and thus

$$(1-L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \frac{d(d-1)(d-2)}{6} x_{t-3} + \dots .$$

Note that if d is an integer value, x_t will be a function of a finite number of past observations, while if d is non-integer, x_t depends upon values of the time series far away in the past. In this context, *d* plays a crucial role since it will be an indicator of the degree of dependence of the time series. Thus, the higher the value of *d* is, the higher the level of association will be between observations.

In this article, we combine fractional integration with non-linear structures. In particular, we consider the methodology developed by Cuestas and Gil-Alana (2015) for testing the order of integration in time series with non-linear deterministic trends that use Chebyshev polynomials in time. We consider the following model:

$$y_t = \sum_{i=0}^{m} \theta_i P_{iT}(t) + x_t, \qquad t = 1, 2, \dots, \tag{2}$$

with *m* indicating the order of the Chebyshev polynomial, and x_t following an I(d) process of the form as in equation (1).

The Chebyshev polynomials $P_{i,T}(t)$ in (1) are defined as:

$$P_{0,T}(t) = 1,$$

$$P_{i,T}(t) = \sqrt{2}\cos\left(i\pi(t-0.5)/T\right), \qquad t = 1, 2, \dots, T; \quad i = 1, 2, \dots . \tag{3}$$

(see Hamming (1973) and Smyth (1998) for a detailed description of these polynomials). Bierens (1997) uses them in the context of unit root testing. According to Bierens (1997) and Tomasevic *et al.* (2009), it is possible to approximate highly non-linear trends with rather low degree polynomials. If *m = 0* the model contains an intercept, if *m = 1* it also includes a linear trend, and if *m > 1* it becomes non-linear -

the higher *m* is the less linear the approximated deterministic component becomes. The estimation and testing results presented in the empirical section are based on Cuestas and Gil-Alana (2015). They proposed a joint specification of (1) and (2) such that using a Lagrange Multiplier (LM) test of the same form as in Robinson (1994), i.e., testing H_o: $d = d_o$, for a given real value d_o, the null model becomes linear with respect to the (non-linear) parameters.The test has under H_o, a standard N(0, 1) distribution.[1]

In the final part of the manuscript we also examine the possibility of structural breaks, and for this purpose, we employ a procedure developed by Gil-Alana (2008) that allows for breaks in the context of I(d) models with the break dates being endogenously determined by the model itself. Using this approach we consider the following model,

$$y_t \;=\; \beta_i{}^T z_t \;+\; x_t\,; \quad (1-L)^{d_i}\, x_t \;=\; u_t\,, \qquad t \;=\; 1,\ldots,T_b^i\,, \quad i=1,\ldots nb, \tag{4}$$

where nb is the number of breaks, y_t is the observed time series, the β_i's are the coefficients corresponding to the deterministic terms; the d_i's are the orders of integration for each sub-sample, and the $T_b{}^i$'s correspond to the times of the unknown breaks.

4. Data and empirical results

In Figures 1 and 2, we display the twelve series with the original data and their log-transformations respectively, with us working with the latter. Data on CO_2 emissions for the twelve countries are obtained from: Carbon Dioxide Information Analysis Center (http://cdiac.ornl.gov/CO2_Emission/timeseries/national), with data ending in 2012 for all the twelve countries. However, based on data availability the data starts in 1902 for China, 1878 for India, 1884 for South Africa, 1901 for Brazil and 1992 for Russia. For

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[1] See Cuestas and Gil-Alana (2015).

the G7 countries, the data start in 1810 for France, 1792 for Germany, 1860 for Italy, 1868 for Japan, 1785 for Canada, 1751 for the UK and 1800 for US. Based on Figure 1, we observe an increase in the CO_2 emissions for all the countries during the whole sample period. In fact, worldwide carbon dioxide emissions are now 150 times higher than in 1850. Furthermore, we observe a decrease in the CO_2 emissions series in most of the G7 countries during the last years of the sample, but not in the BRICS countries. The different behavior of these countries could be explained by the different impact of the last economic crisis on each of the countries, but it could also be due to the different degrees and effectiveness of environmental policies in developed and developing countries. Finally, the data suggest the existence of possible structural breaks and non-linearities in the series, which justifies the methodology we use in this paper.

As is standard practice in the literature discussed above, we too conducted a wide-array of unit root tests, which besides the standard linear unit root tests, also included tests with structural breaks.[1] However, since unit root tests only reveal whether the data is mean- reverting or not, and does not speak on the precise degree of persistence (i.e., short or long-memory), we decided to concentrate on the long-memory approach. In cases of mean-reversion, the long-range dependence methods applied below helps us detect short- or long-memory, i.e., fast or slow-mean reversion or persistence. This is of paramount importance in case of a variable as crucial as the carbon emissions, since a result of mean-reversion with strong persistence in the series, might require strong environmental policy intervention, depending on how persistent the series are. Besides, from a statistical point of view, it is quite well-known that unit

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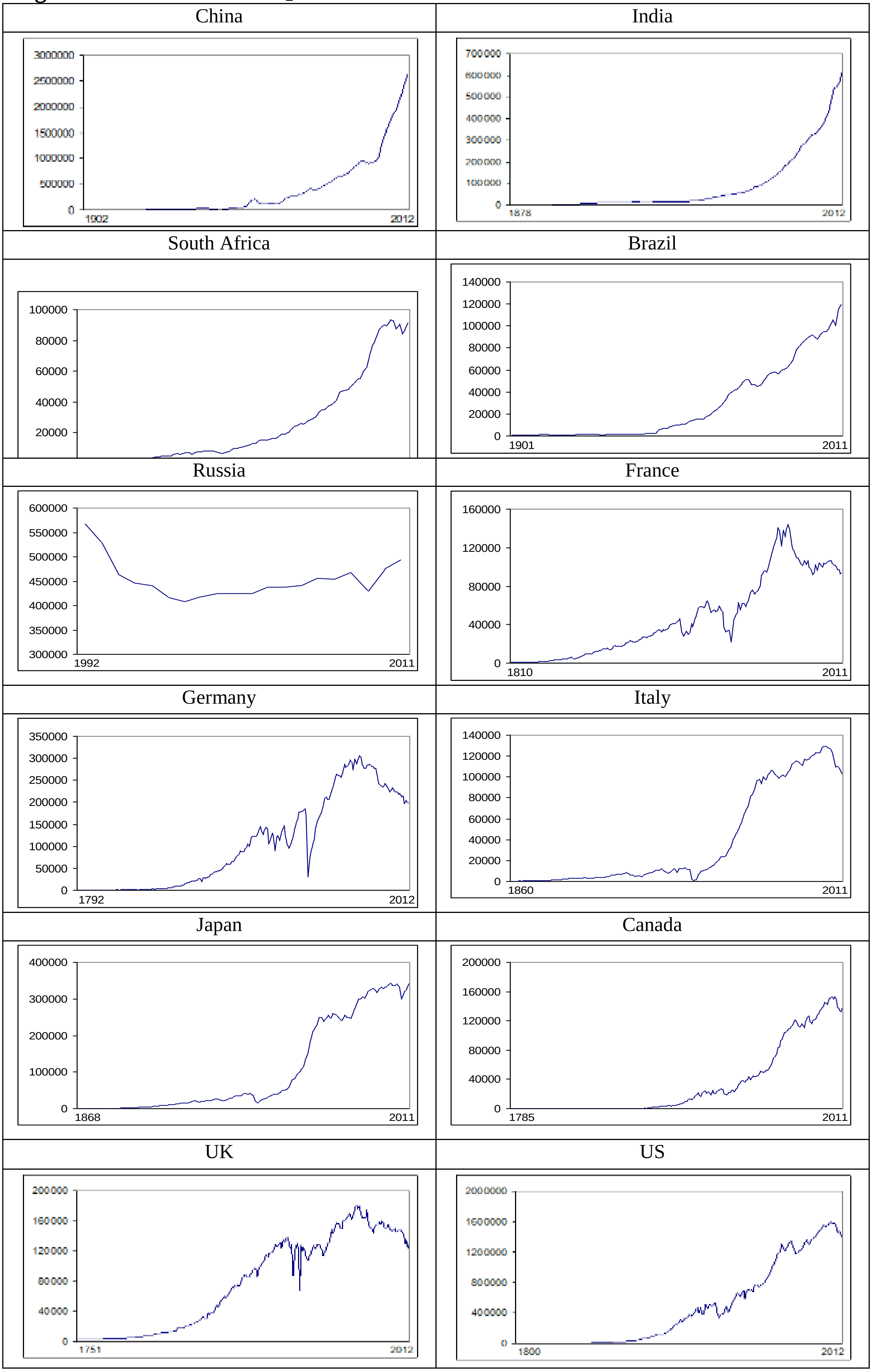
[1] The unit root tests that we conducted includes:the Augmented Dickey Fuller (ADF, 1979), the GLS-detrended Dickey-Fuller (Elliot, Rothenberg, and Stock, 1996), the Phillips-Perron (Phillips and Perron, 1988), the Kwiatkowksi, Phillips, Schmidt, and Shin (KPSS, 1992), the Ng and Perron (NP, 2001). Then we conducted three unit root tests with one (Zivot and Andrews , 1992) and two (Lumsdaine and Papell, 1997 and Lee and Strazicich, 2003) structural breaks. Complete details of these results are available upon request from the authors. However, some discussion of the relevant results can be found in Footnote 2.

Figure 1: Raw data on CO$_2$ emissions



root tests have low power when a series is characterized by a fractional integration process (for a detailed discussion in this regard and more, see Gil-Alana et al., 2015)**.**

In Table 1 we present the estimates corresponding to the model given by (1) and (2), i.e.,

$$y_t \;=\; \sum_{i=0}^{m} \theta_i \, P_{iT}(t) \;+\; x_t , \qquad (1 \,-\, L)^d x_t \;=\; u_t ,$$

with m = 3 to allow for a high degree of non-linear behaviour. We display in the second column the estimates of d (corresponding to the Whittle estimates in the frequency domain, Dahlhaus, 1989), along with the 95% confidence intervals corresponding to the non-rejection values of d, using Cuestas and Gil-Alana (2015). The remaining columns display the estimated coefficients along with their corresponding t-values. We present the results for the two cases of uncorrelated (white noise) and autocorrelated (AR(1)) errors.

The results with respect to the degree of integration are rather similar in the two cases of uncorrelated and correlated errors. Starting with the BRICS, we observe that the estimated values of d are statistically higher than 1 for India and South Africa, while the unit root null cannot be rejected for any of the other three countries. On the other hand, there is almost no evidence of non-linearities, with the only exception of India (where the second non-linear coefficient is found to be significantly different from zero).

If we focus on the G7 countries, only Japan presents an order of integration significantly higher than 1. Then, for the US, France, Italy and the Canada, the unit root null (i.e., d = 1) cannot be rejected, and evidence of mean reversion (d < 1) is obtained in the cases of Germany and the UK, and for the US in the case of autocorrelated errors. Focusing on the nonlinearities, evidence of non-linear behavour is detected in the US, the UK, Germany and France, and partial evidence (with only one of the two non-linear

Table 1: Estimates in an I(d) model with non-linear (m = 3) deterministic terms

i) Uncorrelated errors					
Country	d	θ_0	θ_1	θ_2	θ_3
China	1.09 (0.93, 1.27)	**5.439 (1.71)**	-1.784 (-0.91)	0.074 (0.08)	-0.034 (-0.06)
India	1.11 (1.03, 1.21)	**9.243 (16.17)**	**-1.695 (-4.82)**	0.037 (0.24)	**-0.442 (-4.48)**
Brazil	0.96 (0.81, 1.16)	**8.581 (13.39)**	**-1.811 (-4.78)**	0.077 (0.39)	0.166 (1.23)
S. Africa	1.27 (1.18, 1.40)	**3.921 (1.99)**	-0.981 (-0.47)	-0.281 (-0.36)	-0.347 (-0.75)
Russia	0.38 (-0.61, 1.18)	**13.031 (526.4)**	0.012 (-0.47)	-0.281 (-0.37)	-0.347 (-0.75)
U.S.	0.92 (0.84, 1.02)	**10.570 (28.17)**	**-2.965 (-13.39)**	**-1.052 (-8.67)**	**-0.452 (-5.40)**
U.K.	0.56 (0.49, 0.63)	**10.540 (155.4)**	**-1.350 (-34.02)**	**-0.466 (-15.24)**	**-0.054 (-2.20)**
France	1.01 (0.91, 1.13)	**9.475 (12.87)**	-1.394 (-3.14)	-0.463 (-2.11)	-0.341 (-2.34)
Italy	1.14 (0.92, 1.47)	**3.414 (0.82)**	-1.215 (-0.47)	0.166 (0.15)	-0.196 (-0.28)
Germany	0.64 (0.55, 0.75)	**9.932 (36.09)**	**-2.280 (-14.43)**	**-0.911 (-7.94)**	**-0.328 (-3.65)**
Japan	1.25 (1.13, 1.41)	**4.096 (0.96)**	-1.445 (-0.50)	-0.305 (-0.28)	-0.478 (-0.74)
Canada	1.06 (0.97, 1.16)	**7.812 (4.43)**	-4.516 (-4.20)	-1.060 (-2.11)	0.054 (0.16)
ii) Autocorrelated errors					
Country	d	θ_0	θ_1	θ_2	θ_3
China	1.09 (1.00, 1.18)	**5.438 (1.72)**	-1.799 (-0.88)	0.071 (0.07)	-0.034 (-0.07)
India	1.11 (1.06, 1.17)	**9.243 (16.33)**	**-1.677 (-4.82)**	0.031 (0.22)	**-0.441 (-4.52)**
Brazil	0.95 (0.87, 1.17)	**8.334 (13.69)**	**-1.810 (-4.78)**	0.056 (0.39)	0.165 (1.22)
S. Africa	1.27 (1.12, 1.42)	**3.920 (1.98)**	-0.977 (-0.48)	-0.244 (-0.52)	-0.341 (-0.79)
Russia	0.39 (0.01, 0.86)	**13.227 (516.7)**	0.034 (-0.49)	-0.280 (-0.37)	-0.346 (-0.70)
U.S.	0.92 (0.87, 0.98)	**10.272 (28.13)**	**-2.933 (-13.37)**	**-1.057 (-8.29)**	**-0.434 (-5.33)**
U.K.	0.56 (0.52, 0.61)	**10.223 (155.3)**	**-1.352 (-31.15)**	**-0.482 (-15.21)**	**-0.051 (-2.89)**
France	1.03 (0.90, 1.11)	**9.488 (12.81)**	-1.378 (-3.77)	-0.455 (-2.13)	-0.332 (-2.30)
Italy	1.13 (0.90, 1.43)	**3.419 (0.99)**	-1.210 (-0.55)	0.166 (0.34)	-0.196 (-0.33)
Germany	0.63 (0.53, 0.80)	**9.936 (11.25)**	**-2.277 (-4.47)**	**-0.915 (-1.99)**	**-0.327 (-0.67)**
Japan	1.23 (1.10, 1.40)	**4.091 (1.04)**	-1.443 (-0.51)	-0.301 (-0.27)	-0.471 (-0.74)
Canada	1.06 (0.97, 1.16)	**7.808 (4.11)**	-4.513 (-4.23)	-1.045 (-2.03)	0.077 (0.14)

coefficients being statistically significant) in the case of Canada. Japan and Italy are the only two G7 countries where no evidence of nonlinearities is found.

We can summarize the above results by saying that practically all series display orders of integration equal to or higher than 1, implying evidence of no mean reversion

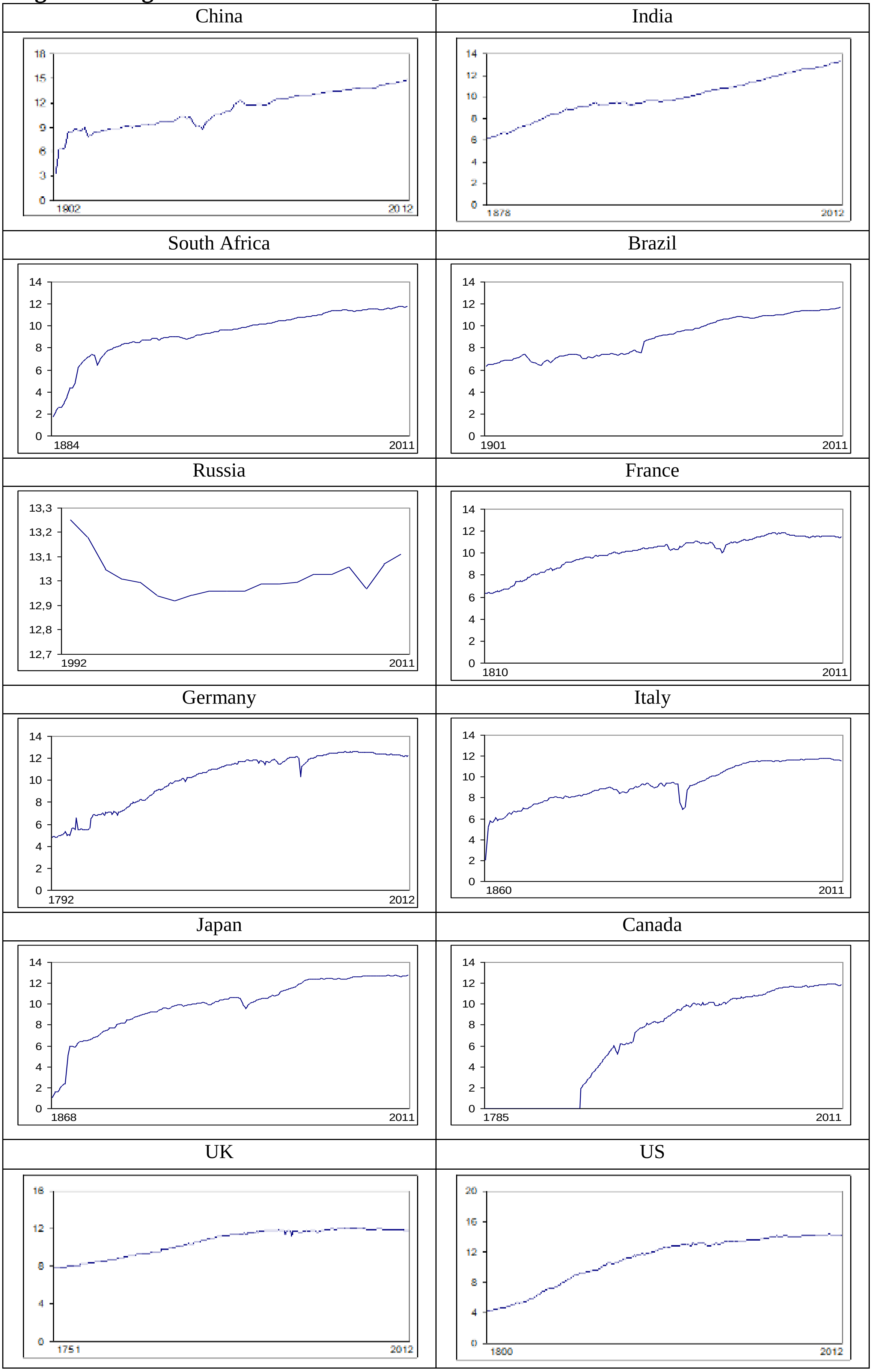
Table 2: Estimates of d with structural breaks following Gil-Alana (2008)

Country	Sub-samples	d	Intercept	Linear trend
China	1902 – 1911	0.13 (-0.72, 1.27)	4.451 (6.58)	0.525 (4.96)
	1911 - 2012	1.19 (0.99, 1.44)	7.799 (45.10)	0.072 (1.86)
India	1878 – 1919	0.85 (0.66, 1.13)	6.181 (96.70)	0.079 (12.91)
	1920 – 1948	0.81 (0.44, 1.35)	9.306 (163.32)	0.013 (2.10)
	1949 - 2012	0.85 (0.69, 1.07)	6.678 (313.20)	0.057 (25.30)
Brazil	1901 – 1949	1.01 (0.73, 1.38)	6.324 (44.82)	0.026 (1.95)
	1950 – 2012	1.17 (1.05, 1.33)	8.521 (162.62)	0.053 (4.23)
S. Africa	1984 – 1899	0.77 (-0.26, 1.41)	1.421 (4.24)	0.385 (7.52)
	1900 – 2012	1.36 (1.23, 1.56)	6.218 (88.89)	0.101 (3.37)
Russia	1992 – 2012	1.07 (0.64, 1.43)	13.019 (271.97)	---
U.S.	1800 - 1824	0.59 (0.24, 1.09)	4.175 (131.36)	0.057 (22.64)
	1825 – 1857	0.78 (0.49, 1.14)	5.633 (85.37)	0.113 (18.44)
	1858 – 1908	0.61 (0.41, 0.91)	9.266 (148.94)	0.066 (24.03)
	1909 - 2012	0.80 (0.68, 0.97)	12.675 (185.22)	0.015 (4.99)
U.K.	1751 – 1830	0.62 (0.48, 0.85)	7.777 (224.02)	0.023 (22.11)
	1831 – 1870	0.25 (0.02, 0.68)	9.684 (397.16)	0.034 (34.14)
	1871 – 1910	0.23 (-0.13, 0.74)	11.113 (644.97)	0.016 (23.85)
	1911 - 2012	0.51 (0.44, 0.61)	11.788 (208.22)	---
France	1810 – 1939	1.03 (0.94, 1.16)	6.327 (74.25)	0.034 (4.07)
	1940 – 2012	0.98 (0.85, 1.16)	10.519 (105.30)	0.012 (1.98)
Italy	1860 – 1942	1.07 (0.75, 1.49)	1.773 (4.84)	0.100 (1.87)
	1943 – 1974	0.87 (0.57, 2.27)	7.422 (23.44)	0.129 (3.37)
	1975 – 2012	1.08 (0.88, 1.34)	11.438 (358.32)	---
Germany	1792 – 1913	0.63 (0.51, 0.77)	4.747 (30.43)	0.060 (17.44)
	1914 – 1944	0.78 (0.56, 1.20)	11.810 (101.99)	---
	1845 – 2012	1.29 (1.13, 1.64)	10.810 (99.67)	0.076 (2.04)
Japan	1868 – 1874	---	---	---
	1875 – 1943	1.09 (0.98, 1.28)	5.909 (68.80)	0.068 (4.63)
	1944 – 1974	1.29 (0.02, 2.24)	10.676 (69.49)	---
	1975 – 2012	0.82 (0.63, 1.11)	12.412 (347.45)	0.008 (2.59)
Canada	1785 – 1846	---	---	---
	1847 – 1919	0.97 (0.83, 1.20)	1.839 (10.47)	0.115 (6.14)
	1920 – 2012	0.90 (0.78, 1.07)	9.721 (133.66)	0.022 (4.49)

and permanent effects of shocks in CO_2 emissions. The only exceptions are Germany, the US and the UK, where shocks will have transitory effects. With respect to the non-linearities, more evidence of non-linear behaviour is obtained in the developed countries, especially in the cases of the US and the UK, Germany and France. Partial evidence is also found in Canada and India. The analysis of structural breaks in the time series behavior of CO_2 series will help us to interpret the above results related to the non-linearities.

Table 2 displays the results using the approach suggested by Gil-Alana (2008). We observe in this table that for China there is a single break at the very beginning of the sample period (1911); for India, there are two breaks: one at 1919 and the other one at 1948. For Brazil and South Africa the break date takes place at 1949 and 1899 respectively, while there is no break in case of Russia (due to the small number of observations used). Referring to the G7 countries, for the US and the UK there are three breaks: at 1824, 1857 and 1908 for the US, and a few years later (1830, 1870 and 1910) for the UK. For France, there is a single break at 1939; two breaks take place for Italy (1942 and 1974), Canada (1846 and 1919) and Germany (1913 and 1944), and three in the case of Japan (1874, 1943, 1974). The structural break in China coincides with the 1911 Revolution, which ended the autocratic monarchy in this country and created significant conditions for social and economic development. The structural breaks in India occur with the Government of India Act in 1919 and with the origin of its Industrial Policy Resolution in 1948, and the consequent economic development and growth of this country. For Brazil, the structural break found in 1949 coincides with the political and economic liberalism measures reintroduced at the end of World War II, while in the case of South Africa the break coincides with the beginning of the South African War (or second Boer War, 1899-1902). Thus, in both countries, the structural breaks in carbon dioxide series are related with changes in economic development or growth of their economies, as expected due to the positive relationship

Figure 2: Log transformations of the CO_2 emissions



China

India

South Africa

Brazil

Russia

France

Germany

Italy

Japan

Canada

UK

US

between the CO_2 emissions and economic development. The structural breaks in the US and the UK in 1908 and 1910 are also related to the economic development, since they occurred after the panic of 1907 in the US, and the increase in economic growth and population growth in the US and the UK in 1910. The rests of the breaks in the G7 countries take place approximately around the War World I (1914-18), War World II (1939-1945) and the first oil price crisis about 1975.

If we focus now on the orders of integration, we observe that the unit root null hypothesis cannot be rejected for any of the subsamples in the cases of China and India. However, for Brazil and South Africa, the unit root null is rejected in favor of higher orders of integration after the structural break. For the US, the unit root hypothesis cannot be rejected for the first two subsamples, being rejected in favor of mean reversion ($d < 1$) for the last two subsamples, i.e., with data starting after 1858; for the UK, evidence of mean reversion is obtained in the four subsamples examined, and the time trend coefficient is found to be statistically insignificant in the last subsample (1911 – 2012). For France, Italy, Japan and Canada, evidence of unit root is found in all subsamples, while evidence of mean reversion is obtained in Germany for the first sub-period. That is, the non-stationary behaviour of CO_2 emissions in the majority of the countries and the mean reversion in the series in the UK, the US and Germany are robust to the inclusion of non-linearities and structural breaks when modeling these series.[2] Figure 2 reproduces the estimated trends for each series. This figure also points to the existence of differences in the actual and expected time trends of CO_2 emissions, suggesting that CO_2 emissions are growing at a higher rate in China, India, Brazil and

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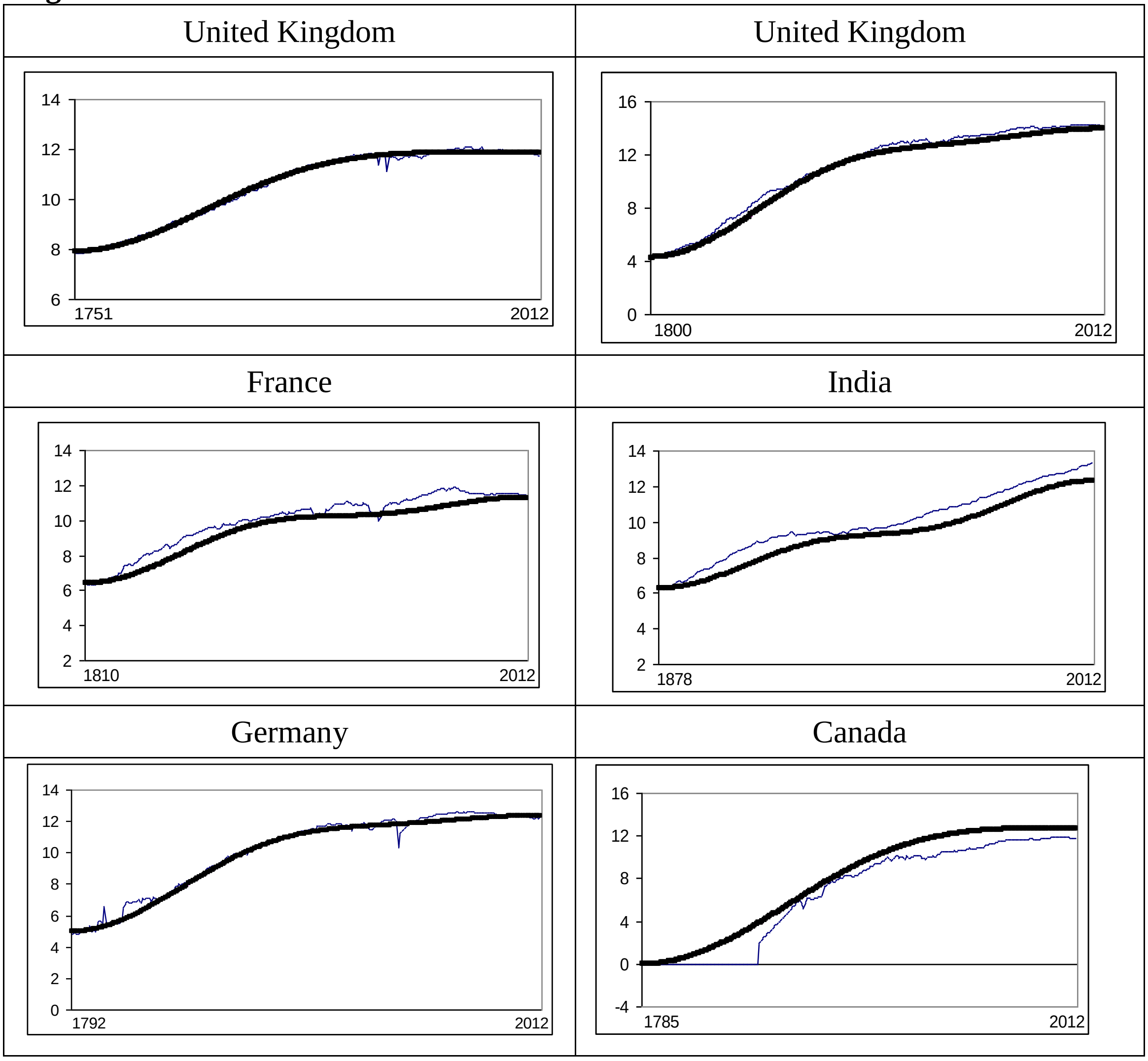
[2] In general, evidence from the standard unit root tests with no breaks were mixed. However, given the long-samples and possibility of structural breaks and nonlinearities (as indicated in our fractional integration model estimations), not much reliance can be placed on the standard unit root tests. If we base our inferences on the most powerful of the unit root tests with breaks, i.e., the Lee and Strazicich (2003) test, amongst the alternatives considered, we observe: (1) For the BRICS, CO_2 emissions in Russia is stationary, and; (2) For the G7, Germany and UK are stationary – a result in line with the fractional integration tests.

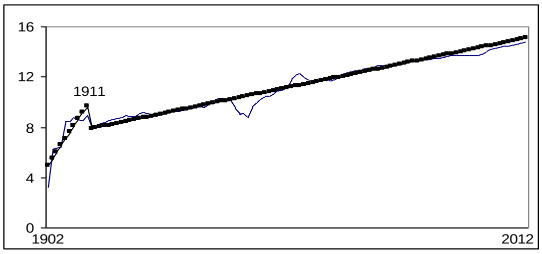
Figure 3: Estimated non-linear trends



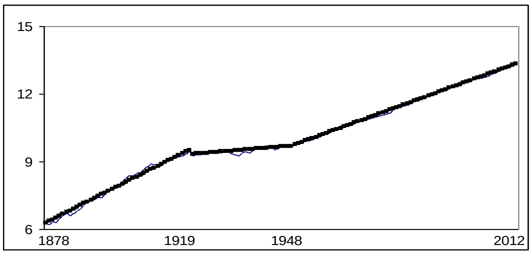
South Africa than in the developed countries. Again, the degree of development of each of the countries is important in the expected growth rate of CO_2 emissions of the analyzed countries. Comparing the non-linear trends presented in Figure 3 with the linear ones in Figure 4, and using several diagnostic tests on the residuals the results support the non-linear specifications in the six cases presented (i.e., the US, the UK, France, India, Germany and Canada), particularly for the US, the UK and Germany. It would also be interesting to test whether significant changes in the parameters of the Chebychev's polynomial occur during the analyzed periods, but this is left for future research.

Figure 4: Estimated linear trends

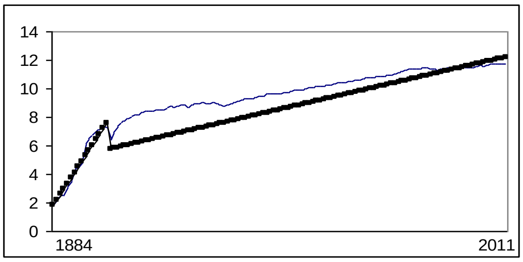
China



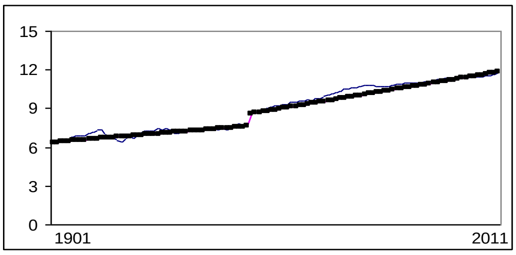
India



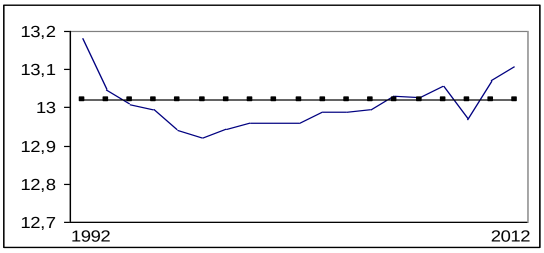
South Africa



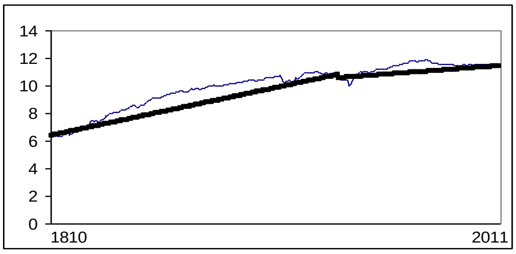
Brazil



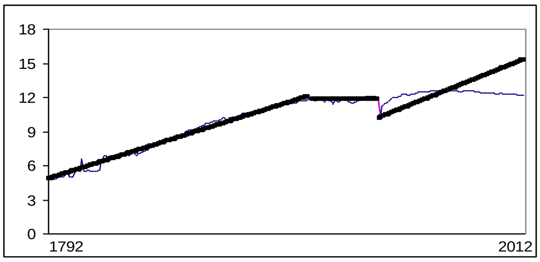
Russia



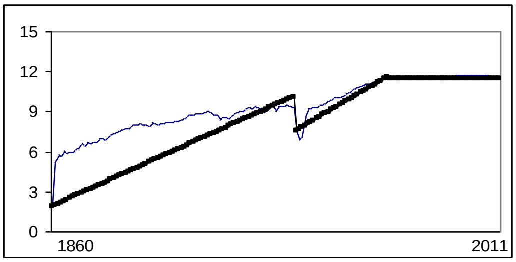
France



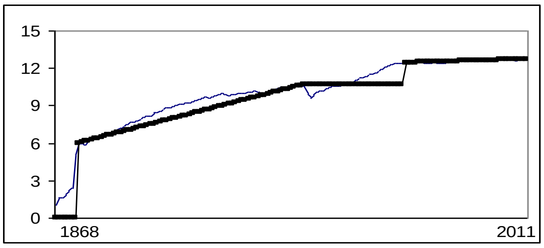
Germany



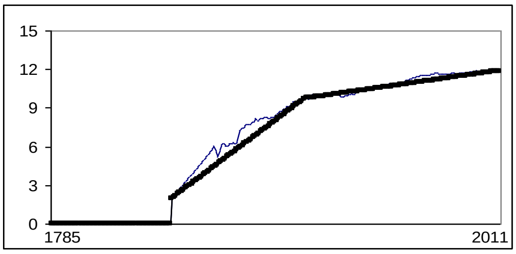
Italy



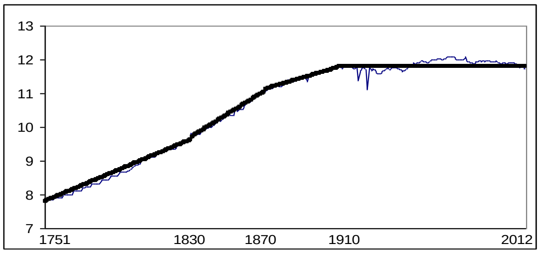
Japan



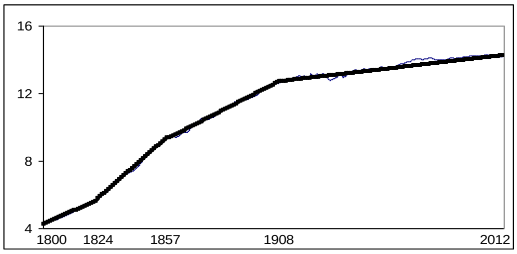
Canada



UK



US



5. Concluding comments

This paper examines the time series behaviour of CO_2 emissions within a long memory approach with non-linear trends and structural breaks using long span of data for the BRICS (Brazil, Russia India, China and South Africa) and the G7 countries (US, UK, France, Italy, Germany, Japan and Canada). In a first step, we combine fractional integration and non-linear deterministic trends using the methodology developed in Cuestas and Gil-Alana (2012), while in a second step we test the order of integration of the CO_2 emissions series allowing for structural endogenous tests using the methodology in Gil-Alana (2008).

The main results in the paper show significant differences in the time series properties of the CO_2 series among the analyzed countries, which are indeed related to their degree of industrialization. First, the results suggest that the carbon dioxide emissions series display, in most of the cases, orders of integration equal to or higher than 1, implying permanent effects of shocks in CO_2 emissions. The only exceptions are Germany, the US and the UK, where shocks will have transitory effects. This result is robust to the inclusion of non-linearities in the deterministic trends and to the existence of structural breaks in the series. Based on these results, stronger policy interventions are recommended in the cases of the BRICS countries, Canada, Italy, France and Japan, given the permanent effects of shocks in the CO_2 emissions in these countries, than in the US, the UK and Germany.

Second, and with respect to the non-linearities, more evidence of non-linear behaviour is obtained in the G7 than in the BRICS countries, especially in the cases of the US, the UK, Germany and France. Partial evidence is also found in Canada and India. Following these results, we could conclude that the CO_2 emissions series in France, the US and the UK have been affected by stronger or more significant disruptions than in the cases of the BRICS and the rest of the G7 countries, where the growth rates (or first differences of the log series) of the CO_2 series are found to be constant over the whole period.

Third, the results show the existence of significant structural breaks in the carbon dioxide series of the analyzed countries. While, structural breaks occur in the first periods of the sample in China (1911), South Africa (1899), the US (1824, 1857, 1908), the UK (1830, 1870, 1910), Canada (1846), Germany (1913) and Japan (1874), we find significant structural changes in India in 1919 (as in the previous countries) and in 1948, coinciding with its gaining independence in 1947 and the origin of its Industrial Policy Resolution in 1948, and the consequent economic development and growth of this country. We also find evidence of structural breaks coinciding with the World War II in the cases of Germany, France and Italy. The structural breaks found in the data suggest the existence of a significant relationship between the economic growth of a country and its degree of development.

Finally, the differences in the degree of integration, together with the differences in the non-linear deterministic trends among the analyzed countries, have important environmental policy implications. For example, the significant different the time series properties of CO_2 emissions in our sample of countries might difficult any convergence process among the CO_2 emissions in these two groups of countries, implying that strong policy interventions should be required to favor a convergence process in carbon dioxide emissions, since our results suggest significant different time series properties. Furthermore, the different degrees of integration found in the series suggest that policy interventions will only have a transitory effect on carbon emissions in some of the countries (i.e., Germany and the UK) while they will have permanent effects on the CO_2 emissions in other countries.

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