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GHG in EUROPE. Evidence of persistence across markets using fractional integration

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ABSTRACT

This paper investigates the persistence of GHG in Europe, evaluating the effectiveness of government policies, including the Kyoto Protocol and the EU Council commitment. Mean reversion properties, and the structure of the integration factor were examined to determine the degree of persistence across markets and assess policy effectiveness. The analysis focuses on CO_2, CH_4, and NO_2 pollutants, with monthly data starting in January 2000 and ending in December 2021 from major European countries, and the US, Japan, Brazil, China, and India for comparison purposes. Empirical results show clear evidence of mean reversion in CO_2 emissions observed across all countries, indicating certain degrees of stabilization. Similar patterns are seen for CH_4, and NO_2, observing reduced persistence of these pollutants; however not all countries exhibit mean reversion properties. Thus, these findings highlight policy progress in stabilizing GHG emissions, particularly for CO_2, but underscore the need for further efforts to achieve a substantial emissions reduction.

1. Introduction

Several recent academic studies highlight the compelling justifications for undertaking an inquiry into the examination of greenhouse gas (GHG) in Europe and the provision of empirical evidence regarding their persistence across markets (Edenhofer et al., 2018; Stavins, 2019). This line of research is essential for understanding the overall trajectory of climate change and developing effective mitigation strategies. In addition, GHG emissions possess profound economic implications, encompassing the costs associated with climate change impacts as well as potential prospects for green growth (Wang and Cao, 2018; Edenhofer et al., 2018 or Wei et al., 2020 among others).

The starting point of the GHG target reduction in Europe was the Kyoto summit in 1997, that led developed countries to agree on a set of GHG emission targets. In particular, the European Community (EC) agreed to 8% reductions during 2008-2012 period compared to 1990 levels (OJEC L130/1, 2002). To assess this target, the EU launched in 2000 the European Climate Change Program (ECCP) and introduced of the European Emissions Trading Scheme (ETS) with national emission caps from power and industry sectors (Directive 2003/87/EC). These limits were formally set in the 2008 Climate and Energy package where the EU Council agreed on the famous set of targets "20-20-20", to reduce 20% GHG emissions and set a share of 20% usage in renewable energies by 2020 (EC, 2008). Apparently, these measures were very successful in Europe as GHG emissions in the European Union have decreased by 34% since 1990 (Tiseo, 2023). In addition, by the end of 2015, the Paris Agreement was signed at the UN Climate Change Conference (COP21), improving upon the previous Kyoto agreement. Basically, its overarching goal is to hold the increase in the global average temperature to well below 2°C above pre-industrial levels and pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels (UNFCC, 2015). Following this new UN agreement, the EC agreed on a more ambitious framework for 2030 with a GHG target of 40% and a target of 27% usage for green energies (compared to 1990 levels), seeking to achieve climate neutrality by 2050 (EC, 2020). Furthermore, some countries such as Germany, aimed to become carbon neutral before this date (Tiseo, 2023) and set their GHG reduction to 65%. To ensure this target, policy measures were oriented to raising CO2 absorption with forests and green spaces, an improvement in building efficiency and specific decarbonization of the energy industry, responsible for 75% of EU GHG emissions (EC, 2022a). The war in Ukraine, started in 2022, has led the EU Commission to introduce modifications with a new

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comprehensive plan, REPowerEU (EC 2022b), to drastically reduce the dependence on Russian energy resources by strengthening energy efficiency, accelerating the buildout of renewable energy, and prioritizing greenhouse gas emissions reductions, but also including security and affordability topics (Prandin, 2022).

Therefore, during the last two decades, the European Union (EU) has consistently assumed a leadership role in climate change policy (Helm, 2020). The main objectives of this paper are twofold. First, to investigate persistence and mean reversion in GHG in recent times, since the year 2000; and second, to use these data to analyze the success of the government policies applied before and after the Kyoto protocol. In particular, the 2008 "20-20-20" commitment, and some other policies in the largest European economies. Mean reversion properties and the structure of the integration factor are some classic econometric techniques that might help to gain an understanding of whether current policies are good enough or if new measures need to be taken. Some authors mention that the persistence of GHG can effectively assess the economic consequences and identify specific industries that need special assistance in transitioning towards low-carbon alternatives (Stavins et al., 2014; McCollum et al. 2018). Along this paper, we provide evidence of mean reversion for the CO2 emissions across all countries under study but not for the other pollutants.

The structure of this paper is as follows: Section 2 presents the literature review on GHG persistence focusing on studies using fractional integration techniques. Section 3 is devoted to data and methodology. Section 4 describes the empirical results and finally, Section 5 concludes the manuscript with the main implications of this study and future lines of research.

2. Literature review

In the specific field between persistence and GHGs, the seminal paper of Banerjee et al. (1993) contributed to the econometric analysis of nonstationary data, providing valuable insights into cointegration and error correction modeling. Lee and Strazicich (2003) introduced a minimum LM unit root test with two structural breaks, which provided a rigorous statistical framework for detecting structural changes and studying long-run relationships. Hafner and Preminger (2009) explored asymptotic theory for multivariate GARCH models, enhancing our understanding of the volatility dynamics and spillover effects in financial and economic time series. More recently, Goh et al. (2017) conducted a comprehensive time series analysis to understand the persistence of GHG emissions. Their study contributed to the ongoing challenges of reducing emissions by providing insights into the persistence patterns and the need for effective policy interventions.

More specifically on integration analysis, Christidou et al. (2013) analyzed the stationarity of carbon CO2 emissions per capita for a global set of 36 countries (1870–2006 period with yearly samples) by applying non-linear unit root tests. Authors found evidence that stationarity is more likely in richer countries that outsourced some of the intensive emission industries. Moreover, it was observed that drastic policy measures could force a non-linear mean-reverting behavior in the series. Thus, economies that have focused on the services sector might provide stronger probabilities for stationarity compared to emerging economies where manufacturing or construction sectors were more important. Furthermore, Tiwari et al. (2016) analyzed with non-linear unit root tests the per capita CO2 emissions for 35 countries in Sub-Saharan Africa (1960–2009 period with annual observations) confirming this empirical evidence of stationarity for development countries. Longer spans for global CO2 emissions (0 b.C. – 2014 with annual data) were used in Erdogan et al. (2022), finding empirical evidence of unit root properties in the time series, and structural breaks in the influenza pandemic (1557) and the invention of the steam engine (1712), thus with clear evidence of non-mean-reverting behavior over this very large period. More recently, Pata and Aydin (2023) used a new wavelet-based nonlinear unit root test to investigate the stationary properties of the per capita CO2 emissions (1868-2014 period, annual data) for the G7 countries, finding evidence that CO2 emissions have a unit root in the frequency domain for all countries, concluding that CO2 emission policies have permanent effects for G7 countries.

Following these studies and delving deeper into fractional integration, Gil-Alana et al. (2017) analyzed with the integration index the long-term behavior of CO2 emissions for the BRICS (Brazil, Russia, India, China and South Africa) and G7 countries (for the last 150-250 years depending on the annual data of each), finding empirical evidence of significant differences in the time series properties related to their degree of industrialization. In particular, most series display orders of integration equal to or higher than one implying permanent effects of shocks in CO2 emissions; however, Germany, the US and the UK show orders of integration smaller than 1 and transitory effects over these shocks. Gil-Alana and Trani (2019) studied most European Union (EU) members, China and the US (1960-2013 with yearly samples), finding evidence of significant positive trends and explosive behavior (i.e., $d > 1$) in most southern countries (Spain, Italy, Greece and Bulgaria). By contrast, as in Gil-Alana et al. (2017) the UK was the exception where CO2 emissions display a significant negative trend and signs of mean reversion properties. After this, Gil-Alana and Monge (2020), analyzed worldwide CO2 emissions (1880-2015 with yearly samples) in terms of the temperature deviations, and obtained a CO2 integration factor of 1.30 throughout the entire period of analysis. Finally, an interesting approach was taken on Claudio-Quiroga and Gil-Alana (2022) by using daily data and only two years of CO2 emissions for G7, EU27 and BRICS during the COVID19 pandemic period (2019-2020). Contrary to other studies, these authors found evidence of mean reversion in all countries as the integration factor ranged between $0.5 < d < 1$ in all series.

In the case of other pollutants, McKitrick (2007) analyzed the stationarity of NO2 in the US (1940-1998) with Granger tests, finding evidence of nonstationary properties. Later, Gil-Alana and Solarin, (2018) analyzed the same time series for the US, confirming empirical evidence of orders of integration substantially higher than 1 in the NO2 series, where the unit root hypothesis cannot be rejected, clearly indicating lack of mean reversion. Solarin and Gil-Alana (2021) studied the persistence of the methane emissions in a group of 36 OECD countries (1750-2014) using fractional integration, concluding that all the series were highly persistent, with orders of integration above 1 in most cases (average order of integration equal to 1.31) and linear and positive trends in approximately half of the cases. One of the implications of these findings is that policies designed for decreasing methane emissions will have a long-term impact in these countries.

These references in terms of the integration factor analysis are summarized in Table 1. It can be seen that most studies have used long and very long span periods with yearly data, with unit root or $d > 1$ results in most cases. However, in a recent study of Claudio-Quiroga and Gil-Alana (2022), that use daily observations and shorter time spans, they obtain values for the integration order substantially below 1. Thus, an increase in the sampling frequency might lead to an interesting study question when analyzing GHGs mid-term series, such as the ones which are the object of the present study.Table 2.

3. Data description and methodology

The datasheet of this paper is built with data taken from Commission, Joint Research Centre (EC-JRC)/Netherlands Environmental Assessment Agency (PBL) from the Emissions Database for Global Atmospheric Research - EDGAR, release 7.0 (Crippa et. al., 2022). Time series were chosen for the largest time series (NO2, CO2 and CH4) with monthly observations starting in January 2000 and ending in December 2021. Selected countries were the largest European countries (Germany, Spain, France, Italy, and the UK), and for comparison purposes the US and Japan were chosen as G7 developed countries, and Brazil, China and India as examples from the BRICs countries under development. Figure 1 displays the plots of all these series under analysis. In the case of CO2,

Table 1
Fractional integration and GHG gases literature review summary.

	Period	Sampling	Countries	Tests	d estimation
CO_2					
Christidou et Al. (2013)	1870–2006	Yearly	Global	Unit root testing	
Tiwari et Al. (2016)	1960–2009	Yearly	Africa	Unit root testing	unit roots
Erdogan et Al. (2022)	0-2014	Yearly	WorldWide	Unit root testing	unit roots
Pata & Aydin (2023)	1868-2014	Yearly	G7	Unit root testing	unit roots
Gil-Alana et Al. (2017)	1750+ - 2014	Yearly	BRICs	Fractional int	d>1
Gil-Alana et Al. (2017)	1750+ - 2014	Yearly	Germany, US, UK	Fractional int	d<1
Gil-Alana and Trani (2019)	1960-2013	Yearly	Spain, Italy, Greece and Bulgaria	Fractional int	d>>1
Gil-Alana and Trani (2019)	1960-2013	Yearly	UK	Fractional int	d<1
Gil-Alana and Trani (2019)	1960-2013	Yearly	Rest EU	Fractional int	unit root
Gil-Alana & Monge (2020)	1880-2015	Yearly	WorldWide	Fractional int	d=1.3
Claudio-Quiroga and Gil-Alana (2022)	2019-2020	Daily	G7, EU27 and BRICs	Fractional int	0.5 < d < 1
NO_2					
Gil-Alana & Solarin, (2018)	1940-1998	Yearly	US	Fractional int	d>1
Adebola and Gil-Alana (2021)	1750-2014	Yearly	36 OECD	Fractional int	d>1 (average 1.31)

Table 2
Descriptive statistics of selected countries. Source Emissions Database for Global Atmospheric Research (EDGAR)

i) CO_2. Monthly emissions by country (kt)										
	SPAIN	GER	FRA	IT	UK	USA	JPN	BRZ	IND	CHI
MIN	19,434	45,552	22,793	23,940	24,430	384,170	79,186	55,208	119,567	337,748
MAX	38,112	109,777	52,208	57,283	57,751	600,704	141,896	130,977	484,986	1,244,489
%growth 2000-2021	-17.79%	-25.92%	-21.79%	-15.83%	-26.37%	-18.02%	-9.43%	77.62%	73.95%	157.77%
CAGR	-0.97%	-1.49%	-1.22%	-0.86%	-1.52%	-0.99%	-0.49%	2.91%	2.81%	4.85%
%growth 2000-2009	-4.56%	-11.21%	-6.77%	-1.47%	-2.88%	-9.32%	-5.88%	55.20%	48.80%	89.45%
CAGR	-0.47%	-1.18%	-0.70%	-0.15%	-0.29%	-0.97%	-0.60%	4.49%	4.05%	6.60%
%growth 2010-2021	-12.39%	-23.88%	-20.01%	-19.75%	-27.58%	-14.81%	-11.30%	10.91%	11.96%	32.64%
CAGR	-1.19%	-2.45%	-2.01%	-1.98%	-2.89%	-1.45%	-1.08%	0.95%	1.03%	2.60%
ii) NO_2. Monthly emissions by country (kt)										
	SPAIN	GER	FRA	IT	UK	USA	JPN	BRZ	IND	CHI
MIN	5.969	9.507	10.158	4.516	6.746	76.818	4.858	35.712	48.550	106.261
MAX	7.404	12.896	13.598	7.978	8.887	84.596	8.208	59.419	84.989	137.150
%growth 2000-2021	-8.33%	-22.03%	-20.55%	-36.31%	-21.48%	-2.23%	-32.27%	63.06%	47.52%	11.14%
CAGR	-0.43%	-1.24%	-1.14%	-2.23%	-1.20%	-0.11%	-1.93%	2.47%	1.96%	0.53%
%growth 2000-2009	-14.35%	-11.59%	-15.42%	-33.56%	-20.94%	-1.57%	-20.98%	22.66%	28.88%	17.00%
CAGR	-1.54%	-1.22%	-1.66%	-4.01%	-2.32%	-0.16%	-2.33%	2.06%	2.57%	1.58%
%growth 2010-2021	3.80%	-12.87%	-9.48%	-3.93%	-1.79%	-3.63%	-16.98%	27.10%	10.50%	-1.28%
CAGR	0.34%	-1.24%	-0.90%	-0.36%	-0.16%	-0.34%	-1.68%	2.20%	0.91%	-0.12%
iii) CH_4. Monthly emissions by country (kt)										
	SPAIN	GER	FRA	IT	UK	USA	JPN	BRZ	IND	CHI
MIN	134.16	196.16	212.07	120.35	147.95	1,824.44	118.16	1,376.90	1,889.27	2,987.05
MAX	153.82	321.75	271.32	187.36	328.78	2,358.29	314.05	2,067.35	2,908.80	7,657.89
%growth 2000-2021	6.79%	-34.40%	-17.76%	-27.68%	-53.57%	-20.79%	-7.43%	47.49%	16.91%	53.41%
CAGR	0.33%	-2.09%	-0.97%	-1.61%	-3.76%	-1.16%	-0.39%	1.96%	0.78%	2.16%
%growth 2000-2009	8.80%	-22.59%	-7.76%	-11.73%	-39.67%	-6.32%	3.06%	22.25%	15.19%	30.56%
CAGR	0.85%	-2.53%	-0.80%	-1.24%	-4.93%	-0.65%	0.30%	2.03%	1.42%	2.70%
%growth 2010-2021	0.93%	-15.24%	-11.86%	-18.80%	-17.41%	-13.26%	-13.63%	17.56%	-1.46%	14.89%
CAGR	0.08%	-1.49%	-1.14%	-1.88%	-1.72%	-1.29%	-1.32%	1.48%	-0.13%	1.27%

developed countries show a low reduction pattern, while BRICs appear to reach a maximum in their emissions and a reduction in their growth rate.

By splitting these time series into decades and focusing in the compound aggregate growth rate (CAGR), it can be seen that all the European countries under analysis, the US and Japan have negative CO2 growth and this reduction had sharpened in recent periods, while BRICs are showing a clear reduction in the growth speed in the last decade. However, in the case of NO2 or CH4 the behavior is not so positive. Some developed countries such as Spain or the UK show flat reductions or increases in the last decade, while in India and Brazil the growth rate is still significant. In the case of CH4, there is a clearer pattern of reduction in all European countries (except Spain), while Brazil and China still maintain patterns of significant growth. Table 1 includes some descriptive statistics and the growth rates of these three periods (2000-2021; 2000-2009 and 2010-2020).

As far as the methodology is concerned, we analyse persistence in time series by using fractional integration methods to estimate the degree of dependence in the data, which is measured by the differencing parameter d. For our purposes we define a covariance stationary process $\{xt, t = 0, \pm1,\ldots\}$ with mean μ as integrated of order 0, and denoted by I(0) if the infinite sum of the autocovariances, defined as $\gamma(u) = E[(x(t) - \mu)(x(t+u) - \mu)]$, is finite, that is,

$$\sum_{j=-\infty}^{\infty} |\gamma(u)| < \infty.$$

This type of processes, also known as short-memory ones, include not only the white noise but also the stationary and invertible AutoRegressive Moving Average (ARMA) model, which is the most frequently

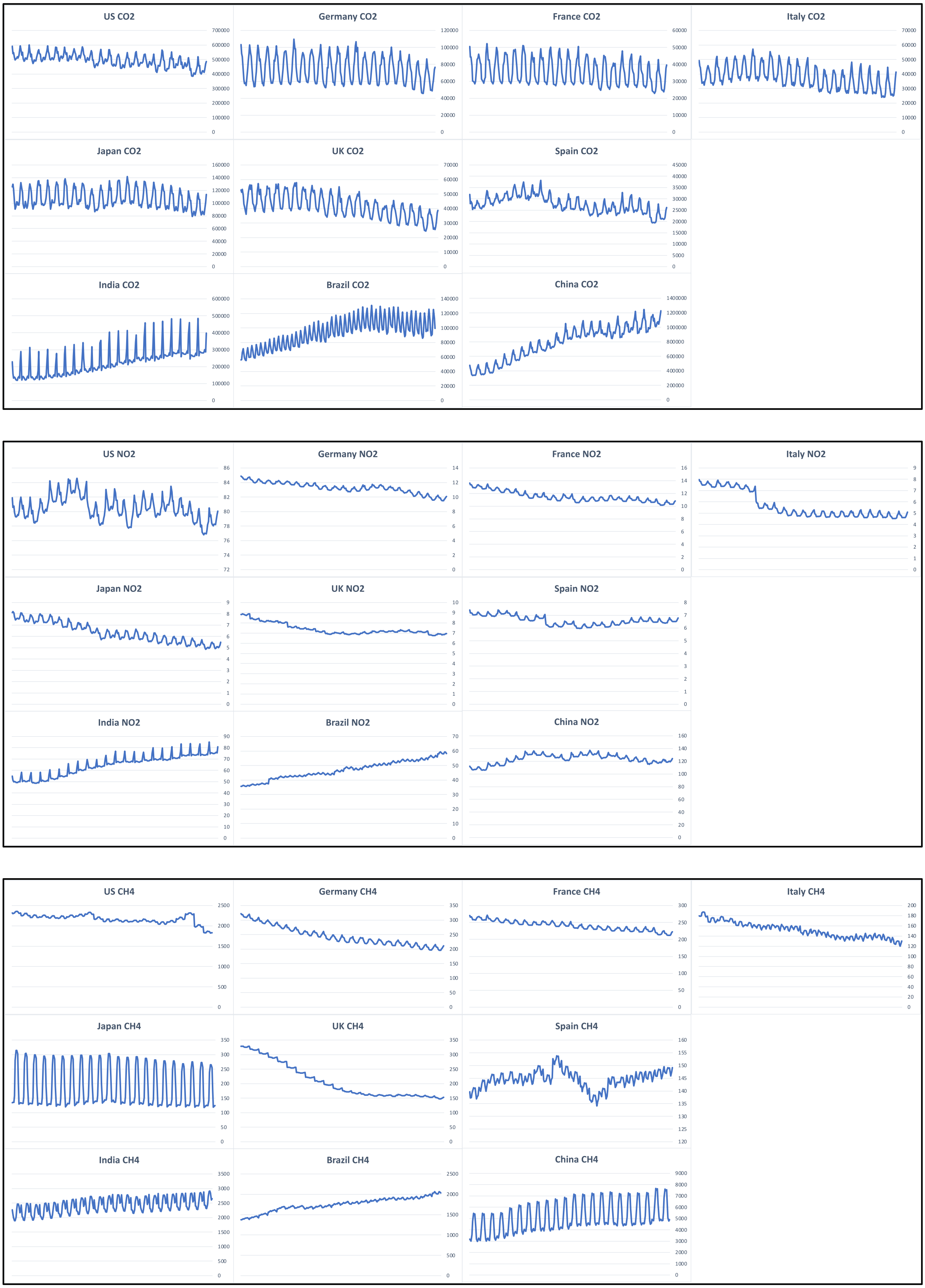

Figure 1. Time series under analysis. Source Emissions Database for Global Atmospheric Research (EDGAR)

used for stationary time series. By contrast, a process displays the property of long memory (so-named because of the relevance of observations in the distant past) if the infinite sum of its autocovariances is infinite:

$$\sum_{u=-\infty}^{u=\infty} \left|\gamma(u)\right| = \infty$$

Within this category of long memory, a standard model widely applied by the time series analysts is the one based on fractional integration or I(d) with a positive order of integration d. A process is said to be integrated of order d, and denoted by I(d), if d-differences are required to make it I(0), i.e.:

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

where B is the backshift operator, and d can be any integer or fractional value. Processes with d higher than 0 are known as long-memory ones because of the high degree of dependence between observations far apart in time.

In particular, the applied model is the following one,

$$y(t) = \alpha + \beta t + x(t), \quad (1 - B)^d x(t) = u(t), \quad t = 1, 2, \ldots \tag{2}$$

where y(t) refers to the observed data, α and β are unknown parameters referring to an intercept and a linear time trend, and x(t) is integrated of an unknown order, d, that is estimated from the data; u(t) is supposed to be an integrated of order 0 process. As European countries tend to increase emissions in winter due to their heating systems this model has been applied including a seasonal AR process for the I(0) u(t) error term. The estimation of the differencing parameter d is crucial to determine if shocks in the series have transitory or permanent effects. Thus, if $d = 0$, $x(t) = u(t)$ in (1), and x(t) is said to be short memory as opposed to the case of long memory that takes place when d is positive. From a statistical viewpoint, the borderline point is 0.5. Thus, if $d < 0.5$, x(t) is covariance stationary; however, if becomes nonstationary for $d \geq 0.5$, and it is more nonstationary as we increase the value of d, noting that the variance of the partial sum increases in magnitude with d; finally, from a policy perspective, mean reversion occurs if $d < 1$ and shocks will have permanent effects if the differencing parameter is equal to or higher than 1. The estimation is conducted via Robinson's (1994) test, which is a Lagrange Multiplier (LM) procedure that relies on the Whittle function in the frequency domain.

This approach (based on Robinson, 1994) is a particular case of a testing procedure that tests the null hypothesis

$$Ho \; d = d_o \tag{3}$$

in the model given by Equation (1) for any real scalar value do. Thus, the confidence intervals reported in the tables in the empirical application below refer to the values of do where the null cannot be rejected. There are several advantages of using this method. First, it is valid for any real value do, and thus, including those values which are away from the stationary case ($do \geq 0.5$) with no need of first differentiation in case of nonstationary data; second, the limit distribution is standard Normal, and this behavior holds independently of the inclusion or not of deterministic terms (like those in the first equality in (1)) and the assumptions made on the error term ut. In addition, the method is the most efficient one in the Pitman sense against local departures. Its functional form can be found in Robinson (1994) for a much more general model, and also in Gil-Alana and Robinson (1994) for the specific modelling approach used in this work.

4. Results

First, we present the results with data from January 2000 until December 2009. Table 3 displays the estimated orders of integration and their associated 95% confidence bands for the three classical cases examined in the unit roots literature of 1) no terms included in the model, 2) with a constant, and 3) with a constant and a linear time trend, and the selected case for each series is shown in the table in bold. This selection is based on the t-values associated to each coefficient, and the estimated values of these selected models are reported in Table 4. Note that the first two equalities in Equation (1) can be expressed as:

$$\widetilde{y}_t = \alpha \widetilde{1}_t + \beta \widetilde{t}_t + u_t, \quad t = 1.2, \ldots \tag{4}$$

where

$\widetilde{y}_t = (1 - L)^d y_t$; $\widetilde{1}_t = (1 - L)^d 1$; $\widetilde{t}_t = (1 - L)^d t$, and u_t is I(0) by construction, so that standard t-values hold in Equation (4).

Focusing first on the time trends, we notice that for CO2 the time trend is only required for India, and the coefficient is positive (see Table 4); for NO2, the time trend is required for Brazil, France, Germany, India, Japan and the UK. However, while the coefficient is negative in the developed countries (France, Germany, Japan and the UK), it is positive for Brazil and India. Finally, for the CH4, the time trend coefficient is significantly negative for France, Germany, and the UK, and positive for India. Thus, for this latter country, the three pollutants

Table 3
Orders of integration[a] with data from Jan-2000 to Dec-2009

Country	No terms	A constant	A linear time trend
i) CO2			
BRAZIL	0.97 (0.85, 1.12)	**0.92 (0.77, 1.10)**	0.93 (0.82, 1.09)
CHINA	0.96 (0.84, 1.12)	**1.01 (0.91, 1.16)**	1.01 (0.88, 1.16)
FRANCE	0.97 (0.85, 1.14)	**0.24 (0.09, 0.45)**	0.23 (0.08, 0.47)
GERMANY	0.97 (0.85, 1.14)	**0.32 (0.19, 0.49)**	0.29 (0.16, 0.50)
INDIA	0.98 (0.85, 1.16)	0.35 (0.26, 0.47)	**0.22 (0.07, 0.41)**
ITALY	0.97 (0.85, 1.15)	**0.60 (0.47, 0.79)**	0.60 (0.47, 0.79)
JAPAN	0.97 (0.85, 1.15)	**0.56 (0.44, 0.75)**	0.56 (0.41, 0.75)
SPAIN	0.97 (0.84, 1.12)	**0.74 (0.59, 0.96)**	0.74 (0.59, 0.96)
UK	0.98 (0.85, 1.14)	**0.49 (0.39, 0.63)**	0.42 (0.31, 0.58)
USA	0.97 (0.84, 1.13)	**0.60 (0.51, 0.73)**	0.56 (0.46, 0.71)
ii) NO2			
BRAZIL	0.96 (0.85, 1.12)	0.96 (0.83, 1.14)	**0.96 (0.84, 1.13)**
CHINA	0.97 (0.84, 1.12)	**1.02 (0.88, 1.24)**	1.03 (0.88, 1.24)
FRANCE	0.97 (0.85, 1.14)	0.79 (0.67, 1.02)	**0.76 (0.59, 1.01)**
GERMANY	0.97 (0.85, 1.14)	0.90 (0.74, 1.22)	**0.89 (0.71, 1.22)**
INDIA	0.97 (0.85, 1.16)	0.61 (0.55, 0.69)	**0.52 (0.44, 0.63)**
ITALY	0.99 (0.85, 1.15)	**1.01 (0.87, 1.20)**	1.01 (0.86, 1.20)
JAPAN	0.99 (0.87, 1.16)	0.86 (0.76, 1.04)	**0.81 (0.67, 1.04)**
SPAIN	0.97 (0.85, 1.12)	**0.95 (0.78, 1.19)**	0.95 (0.77, 1.19)
UK	0.98 (0.87, 1.12)	0.96 (0.82, 1.16)	**0.96 (0.81, 1.16)**
USA	0.97 (0.84, 1.13)	**0.88 (0.75, 1.07)**	0.88 (0.75, 1.07)
ii) CH4			
BRAZIL	0.97 (0.84, 1.12)	**1.00 (0.88, 1.18)**	1.00 (0.88, 1.18)
CHINA	0.97 (0.85, 1.13)	**0.67 (0.56, 0.97)**	0.80 (0.67, 0.97)
FRANCE	0.97 (0.84, 1.13)	0.61 (0.54, 0.73)	**0.52 (0.40, 0.70)**
GERMANY	0.98 (0.85, 1.13)	0.93 (0.80, 1.16)	**0.89 (0.70, 1.17)**
INDIA	0.97 (0.85, 1.13)	0.37 (0.31, 0.45)	**0.38 (0.26, 0.52)**
ITALY	0.98 (0.86, 1.13)	**0.95 (0.79, 1.20)**	0.95 (0.77, 1.20)
JAPAN	0.98 (0.85, 1.16)	**1.21 (0.96, 1.57)**	1.56 (0.96, 1.71)
SPAIN	0.97 (0.85, 1.12)	**0.90 (0.74, 1.10)**	0.89 (0.73, 1.10)
UK	0.98 (0.87, 1.12)	1.04 (0.94, 1.22)	**1.06 (0.92, 1.25)**
USA	0.97 (0.84, 1.13)	**0.98 (0.84, 1.19)**	0.98 (0.84, 1.20)

[a] In the model (1),
$y(t) = \alpha + \beta t + x(t), \quad (1 - B)^d x(t) = u(t), \quad t = 1, 2, \ldots$ α and β are unknown coefficients, referring respectively to a constant and a (linear) time trend results. No terms assume α = β =0, implying the nonexistence of deterministic components. A constant, assumes that only β is supposed to be zero. Finally, a linear time trend is permitted and both coefficients are freely estimated from the data. Then, results are chosen following a minimum error criterion.

Table 4
Estimated coefficients[a] with data from Jan-2000 to Dec-2009.

i) CO2 Country	No terms	A constant	A linear time trend	Seasonality
BRAZIL	0.92 (0.77, 1.10)	10.937 (112.17)	———	0.995
CHINA	1.01 (0.91, 1.16)	13.074 (192.67)	———	0.942
FRANCE	0.24 (0.09, 0.45)*	10.519 (244.66)	———	0.934
GERMANY	0.32 (0.19, 0.49)*	11.232 (204.55)	———	0.940
INDIA	0.22 (0.07, 0.41)*	11.849 (134.68)	0.0030 (2.55)	0.893
ITALY	0.60 (0.47, 0.79)*	10.692 (177.92)	———	0.914
JAPAN	0.56 (0.44, 0.75)*	11.649 (167.0)1	———	0.911
SPAIN	0.74 (0.59, 0.96)*	10.326 (222.11)	———	0.624
UK	0.49 (0.39, 0.63)*	10.765 (203.23)	———	0.931
USA	0.60 (0.51, 0.73)*	13.210 (393.55)	———	0.884

ii) NO2 Country	No terms	A constant	A linear time trend	Seasonality
BRAZIL	0.96 (0.84, 1.13)	3.573 (314.74)	0.0017 (2.00)	0.633
CHINA	1.02 (0.88, 1.24)	4.717 (340.23)	———	0.655
FRANCE	0.76 (0.59, 1.01)	2.604 (171.61)	-0.0015 (-2.96)	0.700
GERMANY	0.89 (0.71, 1.22)	2.555 (252.77)	-0.0010 (-1.82)	0.642
INDIA	0.52 (0.44, 0.63)*	3.929 (113.25)	0.0021 (3.50)	0.900
ITALY	1.01 (0.87, 1.20)	2.077 (76.71)	———	0.474
JAPAN	0.81 (0.67, 1.04)	2.093 (79.76)	-0.0021 (-1.98)	0.854
SPAIN	0.95 (0.78, 1.19)	2.000 (122.87)	———	0.211
UK	0.96 (0.81, 1.16)	2.181 (215.35)	-0.0019 (-2.56)	0.654
USA	0.88 (0.75, 1.07)	4.402 (503.16)	———	0.692

ii) CH4 Country	No terms	A constant	A linear time trend	
BRAZIL	1.00 (0.88, 1.18)	7.228 (637.42)	———	0.857
CHINA	0.67 (0.56, 0.97)*	8.096 (56.88)	———	0.996
FRANCE	0.52 (0.40, 0.70) *	5.584 (514.87)	-0.0007 (-4.02)	0.835
GERMANY	0.89 (0.70, 1.17)	5.774 (394.63)	-0.0022 (-2.70)	0.828
INDIA	0.38 (0.26, 0.52)*	7.662 (170.25)	0.0013 (2.02)	0.954
ITALY	0.95 (0.79, 1.20)	5.191 (271.72)	———	0.724
JAPAN	1.21 (0.96, 1.57)	4.489 (24.76)	———	0.999
SPAIN	0.90 (0.74, 1.10)	4.938 (475.92)	———	0.494
UK	1.06 (0.92, 1.25)	5.798 (356.33)	-0.0041 (-2.14)	0.969
USA	0.98 (0.84, 1.19)	7.747 (859.73)	———	0.536

[a] An asterisk (*) indicates evidence of reversion to the mean at the 95% level.

display a positive trend, while France, Germany and the UK show a negative trend in case of NO2 and CH4. According to these preliminary results based on the deterministic terms, while negative trends, implying a reduction in the emissions, are observed in some developed countries, positive ones are observed in Brazil and India.

Thereafter, we look at the order of integration of the series, and thus, deal with the differencing parameter. For CO2 we observe in the upper panel of Table 4 that the hypothesis of mean reversion is rejected in favor of unit roots only for Brazil and China. Thus, reversion to the mean occurs in all the remaining countries, with values of d significantly below 1 and ranging from 0.22 and 0.24 in the cases of India and France to 0.74 in the case of Spain. Finally, we also observe that the seasonal component is important in all cases, with values for the AR coefficient higher than 0.9 in most cases. For NO2, we observe, however, higher degrees of integration and only India ($d = 0.52$) presents evidence of reversion to the mean. For the rest of the countries, the unit root null hypothesis, i.e., $d = 1$ cannot be rejected. Finally, for CH4, looking at the results in the lower panel of Table 4 we see that mean reversion takes place in the cases of China, India and France and the unit root cannot be rejected in the remaining cases. Seasonality, though relevant, is not as important in NO2 and CH4 as with the CO2 emissions.

Second, we look at the results using the sample from January 2010 to December 2021. Results are displayed across Tables 5 and 6. Starting once again with the time trend coefficients, we observe that for CO2, only Germany, Italy and the UK display a negative trend; for NO2, Germany and Japan are the countries showing a negative trend, while Brazil displays a positive one; and finally, for CH4, France, Germany, Italy and the UK display a negative coefficient while Brazil displays once again a positive one.

Paying now attention to the integration factor “d”, we observe that for CO2 mean reversion occurs in all cases, with orders of integration ranging from 0.33 in Germany and 0.42 in Italy to 0.72 in the US and 0.75 for Spain. For NO2, there are four countries displaying mean reversion: Italy (with $d = 0.46$) and Germany, India and Japan (the three of them with $d = 0.73$). Finally, for CH4, mean reversion occurs for the same four countries as with NO2 (Italy, Germany, India and Japan) along with France. In addition, there is another group of three countries (Brazil, China and Spain) where the value of 1 is at the borderline of the confidence interval. Thus, only the UK and the US display clear evidence of unit roots. Table 7 summarizes these results of the integration factor d with the confidence intervals, while Figure 2 displays the comparison of these results in all countries under analysis.

In general lines, it can be said that these results are similar to those obtained in the recent work of Claudio-Quiroga and Gil-Alana (2022) which obtained values of d substantially below one, with evidence of mean reversion results in most countries under analysis (OECD, US and BRICs). However, that paper should be regarded as an exception as they used daily samples and 2-year spans, unlike most of the works in the field that use yearly data with longer spans (between 50 and 250 years in most cases) and evidence of unit roots or $d > 1$ results (see, e.g., Christidou et al., 2013; Tiwari et al., 2016; Erdogan et al., 2022; Pata and Aydin, 2023; Gil-Alana et al., 2017, or Gil-Alana and Trani, 2019, among many others).

In the present work we have used intermediate elements to assess the recent GHG policies; in particular 10yr spans with monthly samples. Empirical results show a clear reduction in the CO2 integration factor and evidence of mean reversion properties in all the time-series under analysis. This mean reverting evidence might suggest the interesting result that the traditional pattern of CO2 emissions growth might have reached a ceiling nowadays. However further policy efforts should be raised to reduce these levels and reduce the global warming.

Figure 3 displays the differential time series y(t) – y(t-10year) to evaluate the speed of change between these two subperiods. BRICs countries show positive differences but with a negative slope (thus, emissions are reducing becoming more stable); however, the remaining developed countries show negative differences but which are closer to

Table 5
Orders of integration[a] with data from Jan2010 to Dec2021

i) CO2 Country	No terms	A constant	A linear time trend
BRAZIL	0.98 (0.87, 1.11)	**0.83 (0.69, 0.99)**	0.83 (0.70, 0.99)
CHINA	0.97 (0.85, 1.10)	**0.69 (0.57, 0.88)**	0.64 (0.46, 0.88)
FRANCE	0.98 (0.86, 1.11)	**0.47 (0.38, 0.60)**	0.47 (0.34, 0.64)
GERMANY	0.97 (0.86, 1.10)	0.36 (0.30, 0.45)	**0.33 (0.23, 0.48)**
INDIA	0.95 (0.84, 1.09)	**0.66 (0.54, 0.86)**	0.44 (0.29, 0.85)
ITALY	0.98 (0.87, 1.11)	0.48 (0.42, 0.57)	**0.42 (0.30, 0.58)**
JAPAN	0.86 (0.76, 0.98)	**0.50 (0.43, 0.61)**	0.53 (0.43, 0.66)
SPAIN	0.97 (0.86, 1.12)	**0.75 (0.63, 0.92)**	0.74 (0.62, 0.92)
UK	0.98 (0.87, 1.13)	0.61 (0.49, 0.82)	**0.65 (0.50, 0.83)**
USA	0.97 (0.86, 1.11)	**0.72 (0.60, 0.87)**	0.72 (0.60, 0.88)

ii) NO2 Country	No terms	A constant	A linear time trend
BRAZIL	0.97 (0.85, 1.11)	0.93 (0.80, 1.12)	**0.93 (0.79, 1.12)**
CHINA	0.97 (0.85, 1.12)	**0.89 (0.77, 1.06)**	0.89 (0.77, 1.06)
FRANCE	0.98 (0.88, 1.12)	**0.94 (0.77, 1.17)**	0.94 (0.77, 1.17)
GERMANY	0.98 (0.87, 1.12)	0.75 (0.67, 0.90)	**0.73 (0.63, 0.89)**
INDIA	0.96 (0.85, 1.00)	**0.73 (0.64, 0.84)**	0.66 (0.52, 0.82)
ITALY	0.98 (0.87, 1.12)	**0.46 (0.38, 0.59)**	0.47 (0.35, 0.62)
JAPAN	0.98 (0.86, 1.14)	0.72 (0.62, 0.88)	**0.73 (0.61, 0.88)**
SPAIN	0.98 (0.87, 1.15)	**0.95 (0.82, 1.15)**	0.95 (0.82, 1.15)
UK	0.98 (0.87, 1.11)	**0.95 (0.82, 1.15)**	0.95 (0.82, 1.15)
USA	0.98 (0.85, 1.10)	**0.91 (0.76, 1.09)**	0.90 (0.76, 1.09)

ii) CH4 Country	No terms	A constant	A linear time trend
BRAZIL	0.97 (0.85, 1.11)	0.79 (0.68, 1.00)	**0.78 (0.62, 1.00)**
CHINA	0.97 (0.86, 1.13)	**0.83 (0.65, 1.00)**	0.85 (0.73, 1.00)
FRANCE	0.98 (0.85, 1.11)	0.70 (0.62, 0.86)	**0.69 (0.56, 0.85)**
GERMANY	0.98 (0.86, 1.11)	0.55 (0.51, 0.61)	**0.40 (0.31, 0.53)**
INDIA	0.96 (0.85, 1.09)	**0.50 (0.42, 0.62)**	0.46 (0.38, 0.58)
ITALY	0.98 (0.87, 1.12)	0.72 (0.62, 0.86)	**0.68 (0.57, 0.84)**
JAPAN	0.98 (0.86, 1.14)	**0.55 (0.45, 0.68)**	0.35 (0.22, 0.64)
SPAIN	0.97 (0.86, 1.13)	**0.87 (0.77, 1.00)**	0.87 (0.77, 1.00)
UK	0.98 (0.86, 1.11)	0.91 (0.80, 1.07)	**0.91 (0.79, 1.07)**
USA	0.97 (0.86, 1.11)	**0.99 (0.88, 1.14)**	0.99 (0.87, 1.14)

[a] In the model (1), $y(t) = \alpha + \beta t + x(t), \quad (1 - B)^d x(t) = u(t), \quad t = 1, 2, \ldots$ α and β are unknown coefficients, referring respectively to a constant and a (linear) time trend results. No terms assume α = β =0, implying the nonexistence of deterministic components. A constant, assumes that only β is supposed to be zero. Finally, a linear time trend is permitted and both coefficients are freely estimated from the data. Then, results are chosen following a minimum error criterion.

zero at the end of the period with positive slopes in most cases (speed of change is decreasing and current values are similar to those at the end of the decade). Hence, this result and the evidence of mean reversion in the CO2 emissions would suggest the need to apply further policies to achieve even more reductions in these emissions.

Regarding other pollutants, there are fewer integration factor studies in the recent literature, but empirical results appear to be similar to those for CO2. In particular, Gil-Alana and Solarin, (2018) or Adebola and Gil-Alana (2021) used longer spans and yearly samples with evidence of large integration factors (d > 1 in all cases); while our results show evidence of smaller values of d and mean reversion in nearly half of the countries under study. Thus, it appears that the use of more recent time series might imply a reduction of the integration factor even if the differential time-series (see Figure 3) does not develop a clear pattern in all countries as with CO2. For instance, China displays a clear reduction pattern in NO2, while India and Brazil display a more stable pattern. Other European countries such as Italy, Spain or the UK display an initial reduction but a recent growing pattern. In the case of CH4, the pattern tends to be on the negative side (with the exception of the US) and on the positive side for the BRICs countries. Thus, it appears that with these

Table 6
Estimated coefficients[a] with data from Jan2010 to Dec2021

i) CO2 Country	No terms	A constant	A linear time trend	Seasonality
BRAZIL	0.83 (0.69, 0.99)*	11.421 (109.41)	———	0.987
CHINA	0.69 (0.57, 0.88)*	13.710 (272.87)	———	0.848
FRANCE	0.47 (0.38, 0.60)*	10.527 (123.81)	———	0.912
GERMANY	0.33 (0.23, 0.48)*	11.294 (139.98)	-0.0016 (-1.73)	0.940
INDIA	0.66 (0.54, 0.86)*	12.467 (124.18)	———	0.977
ITALY	0.42 (0.30, 0.58)*	10.636 (119.68)	-0.0022 (-2.00)	0.941
JAPAN	0.50 (0.43, 0.61)*	11.631 (177.45)	———	0.861
SPAIN	0.75 (0.63, 0.92)*	10.266 (166.44)	———	0.848
UK	0.65 (0.50, 0.83)*	10.811 (120.92)	-0.0030 (-1.66)	0.881
USA	0.72 (0.60, 0.87)*	13.202 (257.07)	———	0.811

ii) NO2 Country	No terms	A constant	A linear time trend	Seasonality
BRAZIL	0.93 (0.79, 1.12)	3.823 (333.68)	0.0017 (2.41)	0.671
CHINA	0.89 (0.77, 1.06)	4.833 (335.67)	———	0.598
FRANCE	0.94 (0.77, 1.17)	2.477 (158.09)	———	0.511
GERMANY	0.73 (0.63, 0.89)*	2.441 (178.79)	-0.0010 (-2.77)	0.747
INDIA	0.73 (0.64, 0.84)*	4.261 (106.98)	———	0.973
ITALY	0.46 (0.38, 0.59)*	1.602 (87.12)	———	0.911
JAPAN	0.73 (0.61, 0.88)*	1.875 (59.19)	-0.0015 (-1.76)	0.909
SPAIN	0.95 (0.82, 1.15)	1.876 (145.60)	———	0.645
UK	0.95 (0.82, 1.15)	1.955 (277.06)	———	0.221
USA	0.91 (0.76, 1.09)	4.417 (495.08)	———	0.597

iii) CH4 Country	No terms	A constant	A linear time trend	
BRAZIL	0.78 (0.62, 1.00)	7.455 (766.77)	0.0013 (3.57)	0.873
CHINA	0.83 (0.65, 1.00)	8.373 (65.80)	———	0.994
FRANCE	0.69 (0.56, 0.85)*	5.520 (410.39)	-0.0009 (-2.91)	0.768
GERMANY	0.40 (0.31, 0.53)*	5.482 (346.26)	-0.0011 (-6.04)	0.888
INDIA	0.50 (0.42, 0.62)*	7.828 (191.13)	———	0.989
ITALY	0.68 (0.57, 0.84)*	5.065 (214.47)	-0.0014 (-2.68)	0.798
JAPAN	0.55 (0.45, 0.68)*	5.140 (47.69)	———	0.997
SPAIN	0.87 (0.77, 1.00)	4.994 (486.46)	———	0.769
UK	0.91 (0.79, 1.07)	5.219 (562.63)	-0.0013 (-2.59)	0.740
USA	0.99 (0.88, 1.14)	7.656 (472.93)	———	0.285

[a] An asterisk (*) indicates evidence of reversion to the mean at the 95% level.

Table 7
Comparisons across subsamples.[a]

i) CO2

	Differencing parameter d		Time trend β	
Country	2001 – 2010	2010 - 2022	2001 – 2010	2010 - 2022
BRAZIL	0.92 (0.77, 1.10)	0.83 (0.69, 0.99)*	———	———
CHINA	1.01 (0.91, 1.16)	0.69 (0.57, 0.88)*	———	———
FRANCE	0.24 (0.09, 0.45)*	0.47 (0.38, 0.60)*	———	———
GERMANY	0.32 (0.19, 0.49)*	0.33 (0.23, 0.48)*	———	-0.0016 (-1.73)
INDIA	0.22 (0.07, 0.41)*	0.66 (0.54, 0.86)*	0.0030 (2.55)	———
ITALY	0.60 (0.47, 0.79)*	0.42 (0.30, 0.58)*	———	-0.0022 (-2.00)
JAPAN	0.56 (0.44, 0.75)*	0.50 (0.43, 0.61)*	———	———
SPAIN	0.74 (0.59, 0.96)*	0.75 (0.63, 0.92)*	———	———
UK	0.49 (0.39, 0.63)*	0.65 (0.50, 0.83)*	———	-0.0030 (-1.66)
USA	0.60 (0.51, 0.73)*	0.72 (0.60, 0.87)*	———	———

ii) NO_2

	Differencing parameter d		Time trend β	
Country	2001 – 2010	2010 - 2022	2001 – 2010	2010 - 2022
BRAZIL	0.96 (0.84, 1.13)	0.93 (0.79, 1.12)	———	0.0017 (2.41)
CHINA	1.02 (0.88, 1.24)	0.89 (0.77, 1.06)	———	———
FRANCE	0.76 (0.59, 1.01)	0.94 (0.77, 1.17)	———	———
GERMANY	0.89 (0.71, 1.22)	0.73 (0.63, 0.89)*	———	-0.0010 (-2.77)
INDIA	0.52 (0.44, 0.63)*	0.73 (0.64, 0.84)*	0.0030 (2.55)	———
ITALY	1.01 (0.87, 1.20)	0.46 (0.38, 0.59)*	———	———
JAPAN	0.81 (0.67, 1.04)	0.73 (0.61, 0.88)*	———	-0.0015 (-1.76)
SPAIN	0.95 (0.78, 1.19)	0.95 (0.82, 1.15)	———	———
UK	0.96 (0.81, 1.16)	0.95 (0.82, 1.15)	———	———
USA	0.88 (0.75, 1.07)	0.91 (0.76, 1.09)	———	———

iii) CH_4

	Differencing parameter d		Time trend β	
Country	2001 – 2010	2010 - 2022	2001 – 2010	2010 - 2022
BRAZIL	1.00 (0.88, 1.18)	0.78 (0.62, 1.00)	———	0.0013 (3.57)
CHINA	0.67 (0.56, 0.97)*	0.83 (0.65, 1.00)	———	———
FRANCE	0.52 (0.40, 0.70) *	0.69 (0.56, 0.85)*	-0.0007 (-4.02)	-0.0009 (-2.91)
GERMANY	0.89 (0.70, 1.17)	0.40 (0.31, 0.53)*	-0.0022 (-2.70)	-0.0011 (-6.04)
INDIA	0.38 (0.26, 0.52)*	0.50 (0.42, 0.62)*	0.0013 (2.02)	———
ITALY	0.95 (0.79, 1.20)	0.68 (0.57, 0.84)*	———	-0.0014 (-2.68)
JAPAN	1.21 (0.96, 1.57)	0.55 (0.45, 0.68)*	———	———
SPAIN	0.90 (0.74, 1.10)	0.87 (0.77, 1.00)	———	———
UK	1.06 (0.92, 1.25)	0.91 (0.79, 1.07)	-0.0041 (-2.14)	-0.0013 (-2.59)
USA	0.98 (0.84, 1.19)	0.99 (0.88, 1.14)	———	———

[a] An asterisk (*) indicates evidence of reversion to the mean at the 95% level.

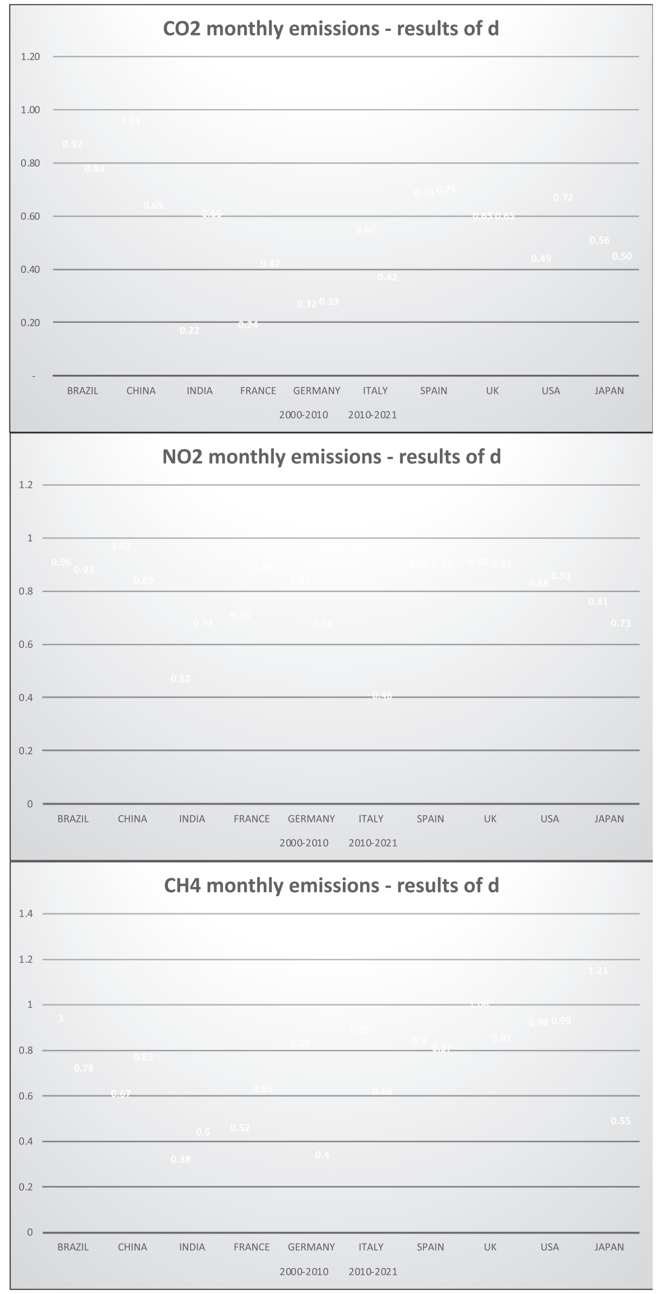

Figure 2. Time series under analysis. Source Emissions Database for Global Atmospheric Research (EDGAR)

pollutants as well, even a higher effort would be needed to homogenize the behavior of the differential time series and to reach smaller values of d. Table 8 summarizes the value of the integration factor by region for each of the two subsamples. A certain convergence can be observed in the integration factor across regions, with a significant reduction in the degree of integration in case of the CH4, in particular in the US-Japan region but also in Europe. We also observe a clear reduction in the standard deviation in the BRICs countries in the three pollutants.

5. Conclusions

In this paper we have examined GHG persistence in recent times, using data starting in the year 2000, at the time of the Kyoto protocol, to analyze the success of the government policies applied in the last two decades. The structure of the integration factor and the mean reversion

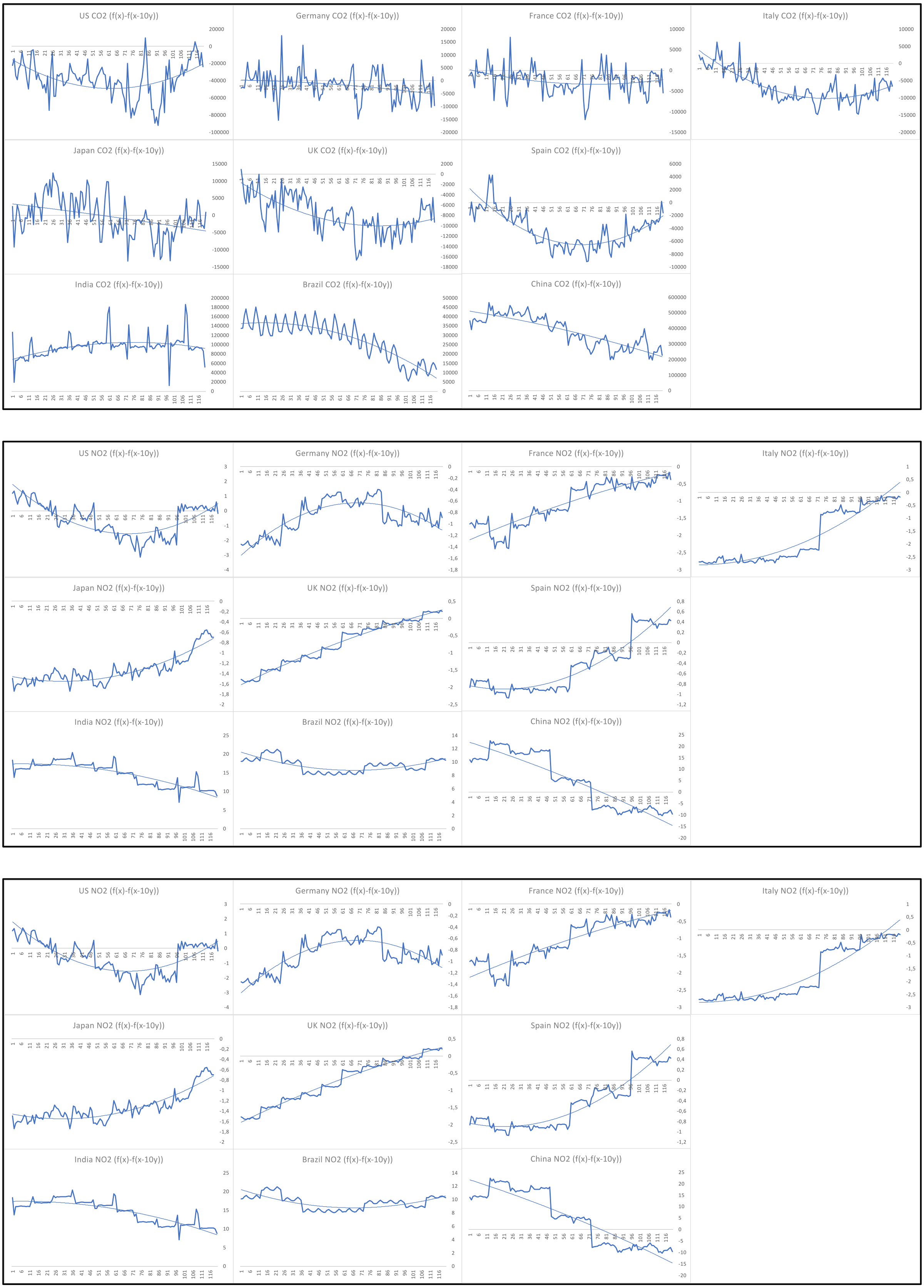

Figure 3. Differences of the subperiods under analysis y(t)-y(t-10_y)

Table 8
Aggregation of integration factor results across group of countries

Average d	CO2 2000-2009	2010-2020	NO2 2000-2009	2010-2020	CH4 2000-2009	2010-2020
BRZ-IND-CHI	0.72	0.73	0.83	0.85	0.68	0.70
EUR	0.51	0.52	0.91	0.81	0.86	0.71
US-JPN	0.53	0.61	0.85	0.82	1.10	0.77
Average	0.58	0.60	0.88	0.82	0.86	0.72
Desv STD						
BRZ-IND-CHI	0.35	0.07	0.22	0.09	0.25	0.15
EUR	0.19	0.15	0.09	0.19	0.18	0.18
USA-JPN	0.04	0.11	0.04	0.09	0.12	0.22
Average	0.26	0.15	0.14	0.15	0.24	0.18

properties of the series were investigated to understand if current policies were sufficent to correct GHG emission growth or if new measures need to be taken. The data used were obtained from the latest EDGAR database release (Crippa et. al., 2022)).

Empirical results in CO2 emissions show that even though previous studies using longer time spans (with data starting before 1950s) found evidence of no mean reversion properties in CO2 emissions; this study, which uses time spans starting in the 2000s with higher sampling frequencies, shows clear evidence of mean reversion in CO2 emissions in all countries. Thus, a clear stabilization appears with a ceiling in the growth of these emissions. The analysis of other pollutants such as CH4 and NO2 show a similar behavior, with a clear reduction of the integration factor in all countries with regards to longer timespans. However not all countries display mean reversion properties.

Therefore, even though policymakers have been succeeding in stabilizing the GHG growth (in particular CO2), a second stage of further effort would be needed to implement a major reduction in these emissions. Future studies may analyze the potential presence of non-linearities or structural breaks to check trend changes and associate them with the applied GHG policies. As these two issues interconnected long memory (and fractional integration) and non-linearities (Granger and Hyung, 2004; Diebold and Inoue, 2001, and many others) these can be substituted by alternatives models that might include Chebyshev polynomials in time (Cuestas and Gil-Alana, 2016), neural networks (Yaya et al., 2021) or Fourier functions (Gil-Alana and Yaya, 2021). Using these approaches we avoid the abrupt changes produced by the structural breaks models and therefore reproduce the behavior of the data in a much smoother way. Work in this direction is now in progress.

CRediT authorship contribution statement

Juan Infante: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing. **Luis A. Gil-Alana:** Conceptualization, Formal analysis, Funding acquisition, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Miguel A. Martin-Valmayor:** Funding acquisition, Data curation, Investigation, Writing – original draft, Writing – review & editing, Project administration, Resources.

Declaration of competing interest

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Data availability

Data will be made available on request.

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References

Banerjee, A., Dolado, J.J., Galbraith, J.W., Hendry, D.F., 1993. Co-integration, error correction, and the econometric analysis of non-stationary data. Oxford University Press.
Christidou, M., Panagiotidis, T., Sharma, A., 2013. On the stationarity of per capita carbon dioxide emissions over a century. Econ. Model. 33, 918–925. https://doi.org/10.1016/j.econmod.2013.05.024.
Claudio-Quiroga, G., Gil-Alana, L.A., 2022. CO2 emissions persistence: evidence using fractional integration. Energ. Strat. Rev. 43.
Crippa et. al. (2022). Emissions Database for Global Atmospheric Research. DOI: https://data.europa.eu/doi/10.2904/JRC_DATASET_EDGAR.
Cuestas, J.C., Gil-Alana, L.A., 2016. A nonlinear approach with long range dependence based on Chebyshev polynomials. Stud. Nonlinear Dyn. Econom. 23, 445–468.
Diebold, F.X., Inoue, A., 2001. Long memory and regime switching. J. Econ. 105 (1), 131–159.
European Commission (2008). COM(2008) 30 final. 20 20 by 2020. Europe's climate change opportunity. Communication from the Commission to the European parliament, the Council, the European Economic and Social Committee and the Committee of the Regions.https://eurlex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2008:0030:FIN:en:PDF. Last view, June 5, 2023.
European Commission (2020). Stepping up Europe's 2030 climate ambition. SWD(2020) 177 final. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020SC0177 Last viewed June 06, 2023.
European Commission (2022a). 5 facts about the EU's goal of climate neutrality. https://www.consilium.europa.eu/en/5-facts-eu-climate-neutrality/ Last viewed June 6th, 2023.
European Comission (2022b). Communication from the commission to the European Parliament, the European Council, the council, the European economic and social committee and the committee of the regions. REPowerEU Plan. https://eur-lex.europa.eu/legalcontent/EN/TXT/?uri=COM%3A2022%3A230%3AFIN&qid=1653034026255#document2 Last viewed June 6th, 2023.
EDGARv7.0_GHG website (https://edgar.jrc.ec.europa.eu/dataset_ghg70). Last view on May 15th, 2023.
Erdogan, S., Pata, U.K., Solarin, S.A., et al., 2022. On the persistence of shocks to global CO2 emissions: a historical data perspective (0 to 2014). Environ. Sci. Pollut. Res. 29, 77311–77320. https://doi.org/10.1007/s11356-022-21278-8.
Gil-Alana, L.A., Monge, M., 2020. Global CO2 emissions and global temperatures: are they related. Int. J. Climatol. 40 (15), 6603–6611. https://doi.org/10.1002/joc.6601.
Gil-Alana, L.A., Solarin, S.A., 2018. Have US environmental policies been effective in the reduction of US emissions? a new approach using fractional integration. Atmos. Pollut. Res. 9 (1), 53–60. https://doi.org/10.1016/j.apr.2017.06.008.
Gil-Alana, L.A., Trani, T., 2019. Time Trends and Persistence in the Global CO2 Emissions Across Europe. Environ. Resour. Econ. 73, 213–228. https://doi.org/10.1007/s10640-018-0257-5.
Gil-Alana, L.A., Cunado, J., Gupta, R., 2017. Persistence, mean-reversion and non-linearities in co2 emissions: evidence from the BRICs and g7 countries. Environ. Resour. Econ. 67 (4), 869–883. https://doi.org/10.1007/s10640-016-0009-3.
Gil-Alana, L.A., Yaya, O.S., 2021. Testing fractional unit roots with non-linear smooth break approximations using Fourier functions. J. Appl. Stat. 48 (13–15), 2542–2559.
Goh, K.T., Lai, W.T., Newbery, D., 2017. Persistence of greenhouse gas emissions: A time series analysis. Energy Policy 104, 47–56.
Granger, C.W.J., Hyung, N., 2004. Occasional structural breaks and long memory with an application to the S&P 500 absolute stock returns. J. Empir. Financ. 11 (3), 399–421.
Hafner, C.M., Preminger, A., 2009. On asymptotic theory for multivariate GARCH models. J. Multivar. Anal. 100 (9), 2044–2054.
Helm, D., 2020. Net zero and the role of the EU. Oxf. Rev. Econ. Policy 36 (S1), S63–S71.
Lee, J.W., Strazicich, M.C., 2003. Minimum LM unit root test with two structural breaks. Rev. Econ. Stat. 85 (4), 1082–1089.
McCollum, D.L., et al., 2018. Energy investment needs for fulfilling the Paris agreement and achieving the sustainable development goals. Nat. Energy 3 (7), 589–599.
McKitrick, R., 2007. Why did US air pollution decline after 1970? Empir. Econ. 33 (3), 491–513.
Pata, U.K., Aydin, M., 2023. Persistence of CO2 emissions in G7 countries: a different outlook from wavelet-based linear and nonlinear unit root tests. Environ. Sci. Pollut. Res. 30, 15267–15281. https://doi.org/10.1007/s11356-022-23284-2.

Prandin, F- (2022). EU climate policy amid Russia's war in Ukraine: A critical overview of key REPowerEU challenges and trajectories towards net-zero. https://www.globsec.org/what-we-do/publications/eu-climate-policy-amid-russias-war-ukraine-critical-overview-key-repowereu. Last viewed June 6th, 2023.
Robinson, P.M., 1994. Efficient Tests of Nonstationary Hypotheses. J. Am. Stat. Assoc. 89 (428), 1420–1437. https://doi.org/10.1080/01621459.1994.10476881.
Solarin, S.A., Gil-Alana, L.A., 2021. Persistence of methane emission in OECD countries for 1750–2014: a fractional integration approach. Environ. Model. Assess. 26 (4), 497–509. https://doi.org/10.1007/s10666-020-09743-5.
Stavins, R.N., et al., 2014. International cooperation: Agreements and instruments to address climate change. In: Field, C.B. (Ed.), Climate change 2014: Mitigation of climate change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, pp. 1371–1434.
Stavins, R.N., 2019. The global architecture of climate change agreements: From coordination to cooperation. Rev. Environ. Econ. Policy 13 (1), 77–93.
Tiseo, I., 2023. Emissions in the EU - Statistics & Facts. Statista.
Tiwari, A.K., Kyophilavong, P., Albulescu, C.T., 2016. Testing the stationarity of CO2 emissions series in sub-saharan african countries by incorporating nonlinearity and smooth breaks. Res. Int. Bus. Financ. 37, 527–540. https://doi.org/10.1016/j.ribaf.2016.01.005.
United Nations for the Climate Change - UNFCC (2015). The Paris Agreement. Taken from https://unfccc.int/sites/default/files/english_paris_agreement.pdf Last viewed June 6th, 2023.
Wang, H., Cao, L., 2018. Regional convergence of carbon dioxide emissions in China. Sustainability 10 (5), 1584.
Wei, Y., et al., 2020. Examining the trade-off between economic growth and environmental quality: A study of China's carbon emission reduction and its economic impact. J. Clean. Prod. 277, 124186.
Yaya, O.S., Ogbonna, A.E., Furuoka, R., Gil-Alana, L.A., 2021. A new unit root test for unemployment hysteresis based on the autoregressive neural network. Oxf. Bull. Econ. Stat. 83 (4), 960–981.