How Do Carbon Emissions Respond to Economic Shocks? Evidence from Low-, Middle- and High-Income Countries

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Abstract: In this study, we examine the stationarity of CO_2 emissions per capita for 98 low-, middle- and high-income countries from 1975 to 2014. To this end, we conduct the nonlinear unit root test developed by Kruse (2011) given that nearly half of the series exhibit nonlinear behaviour over the time period. This empirical evidence provides support for the non-stationarity hypothesis that 50% of CO_2 emissions are from middle-income countries. For the robustness check, we use the panel unit root tests described by Carrion-i-Silvestre et al. (2005) and Bai and Carrion-i-Silvestre (2009), which allow for structural breaks and cross-section dependence. The results provide evidence of stationarity for all three income groups.

Keywords: CO_2 emissions, Stationary, Global level

1. Introduction

The issue of climate change is as old as human history, and one of the greatest challenges of the 21st century is to stabilize the global climate (WRI, 2015). Since 1751 and 1901, carbon emissions increased from 11 million to 2023 million metric tons (http://www.statista.com/). These emissions reached 9453 million metric tons in 1961 and increased to 25381 million metric tons in 2001. Since 1970, emissions due to increases in fossil fuel combustion and global industrialization have increased by 90% and 78%, respectively (Boden et al., 2015). In 2014, carbon emissions were assessed at 36131 million metric tons, indicating the degree to which greenhouse gases have contributed to global warming.

Due to rising concerns over climate change, the interest in testing the stationarity properties of CO_2 emissions per capita at the international level has increased, thus reflecting the importance policy makers, practitioners and academics are awarding global warming. The interest in the alterations of global climate has manifested in policy debates and in recent energy economics literature (Christidou et al. 2013). Examining the stationarity properties of CO_2 emissions per capita can be a source of additional information on global warming as well as on the green effect (Barros et al. 2016). Furthermore, the stationarity of CO_2 emissions per capita indicates that the global warming shocks are transitory, a premise that is similar to the concept of convergence[1]. The non-stationarity of CO_2 emissions per capita may reflect the adoption of weak policy decisions in addressing environmental quality (Barros et al. 2016). Finally, policy makers would benefit from the stationarity properties, if they exist, as they are relevant to the distribution of carbon emissions among nations in the future (Li et al. 2014).

We use a dataset of 98 low-, middle- and high-income countries who are at different stages of economic development. The developed countries have shifted their economies from focusing on the manufacturing and industrial sectors to providing more services, which has resulted in a reduction in CO_2 emissions due to a decline in manufacturing activity. On the contrary, CO_2 emissions have increased with the expansion of the manufacturing sector and industrialization in developing economies as well as with the reduction in the size and importance of the agricultural sector. Understanding the industrial structural change requires

[1]See Ghassen et al. (2015) and Wu et al. (2016) for more details.

the investigation of the stochastic behaviour of CO_2 emissions of low-, middle- and high-income countries.

Testing the unit root behaviour of CO_2 emissions has policy implications. For example, a stationarity of CO_2 emissions indicates that shocks to CO_2 emissions are temporary, i.e., a policy of CO_2 emissions reduction has a temporary effect as CO_2 emissions revert to the trend path in the long term (Li et al. 2014). This presents a serious issue for low-, middle- and high-income countries as they attempt to control the mean value or the trend path in the long term rather than to reduce CO_2 emissions in the short term. Similarly, it is noted that CO_2 emissions containing a unit root have important policy implications for practitioners as they establish guidelines. For example, if CO_2 emissions have a unit root stochastic behaviour, then shocks to CO_2 emissions are permanent. This reveals that policies aimed at reducing CO_2 emissions will have permanent effects and that CO_2 emissions converge to an equilibrium path in the long term. Additionally, strong policy interventions are needed to control the permanent effects of CO_2 emissions. Nelson and Plosser (1982) note that a stationary or a trend stationary process of CO_2 emissions not only has important policy implications but is also important for modelling, testing and forecasting future emissions. This shows that an empirical investigation of unit root properties of CO_2 emissions is important for policy makers and investors alike. However, the standard unit root tests such as ADF (Dickey and Fuller, 1981), PP (Philips and Perron, 1988), DF-GLS (Elliott et al. 1996) and Ng-Perron (Ng-Perron, 2001), as well as the first generation panel tests often applied to check the stationarity properties of CO_2 emissions per capita for panels, are not free of criticism since they fail to accommodate structural breaks and cross-section dependence.

Our contribution to the empirical literature is twofold. First, we conduct the new nonlinear unit root test developed by Kruse (2011) for the series to observe the nonlinear behaviour. Second, we apply the recently developed panel unit root tests (Carrion-i-Silvestre et al. 2005 and Bai and Carrion-i-Silvestre, 2009) that allow for structural breaks and cross-section dependence, and we find that CO_2 emissions include a stationary process.

The remainder of this paper is structured as follows. Section 2 provides a review of the related literature. Section 3 presents the econometric methodology used in this research. Section 4 describes the data and discusses the empirical results. Section 5 concludes the paper and draws policy implications.

2. Review of the related literature

Numerous studies are available in the existing literature regarding the testing of the stationarity properties of CO_2 emissions per capita. Among these studies, Sung and Wang (1996) use data that span 129 years, i.e., 1860 to 1988, to examine the stationarity properties of CO_2 emissions per capita at the global level. They find that by applying the ADF unit root test on first differencing, i.e., I(1), this variable is stationary[2]. Later, Strazicich and List (2003) examine the stochastic behaviour of CO_2 emissions per capita using the Im et al. (IPS, 2002) panel unit root test, and their empirical results indicate that shocks to CO_2 emissions per capita are permanent. Conversely, Nguyen-Van (2005) documents that CO_2 emissions per capita are found to be stationary for 100 countries for the period 1966 to 1996, supporting the convergence hypothesis. Aldy (2006) uses data from 88 countries to test the stationarity properties of CO_2 emissions per capita by using traditional unit root tests such as the DF-GLS (Elliott et al. 1996) and N-P (Ng-Perron, 2001). They find that CO_2 emissions per capita include a stationary process. Moreover, Bulte and Strazicich (2007) report that the stationarity of CO_2 emissions per capita is an indication of structural changes in parameters. Similarly, Lee et al. (2008) re-examine the stationarity properties of relative per capita CO_2 emissions in 21 OECD countries by using the SURADF panel unit root test for the period 1960 to 2000. They report that the relative per capita CO_2 emissions in the OECD countries are a mixture of I(0) and I(1) processes and that 14 out of the 21 OECD countries exhibit divergence. Their results further unveil that conventional panel unit root tests may lead to misleading inferences that are biased towards stationarity even if only one series in the panel is strongly stationary. By applying the KPSS structural break unit root test, Romero-Ávila (2008) revisit the stationarity behaviour of per capita CO_2 emissions using data for 23 OECD countries. The results reveal that the per capita CO_2 emissions contain stationarity for all countries except for Australia, Luxemburg and Portugal. For industrialized countries, Chang and Lee (2008) applied the ADF, PP, DF-GLS and N-P unit root tests to examine whether

[2]The ADF unit test provides ambiguous empirical results due to its low explanatory power (Shahbaz et al., 2014). The ADF test rejects the null hypothesis when it is true and vice versa.

shocks to CO_2 emissions per capita are transitory or permanent. Their results indicate that shocks to per capita carbon emissions are transitory in Greece, Italy and the Netherlands, but the results by Lee and Strazicich (2004) support the view that CO_2 emissions per capita are stationary in the presence of structural breaks. Barassi et al. (2008) re-examine whether the shocks to CO_2 emissions are transitory or permanent. By applying the cross-sectional dependence unit root test, they note that CO_2 emissions exhibit stationary behaviour.

Apart from that, Barassi et al. (2009) re-examine the stochastic behaviour of per capita CO_2 emissions by applying the ADF and IPS unit root tests for 21 OECD countries. They find evidence that the per capita CO_2 emissions contain a unit root problem for all 21 OECD countries except Belgium and the Netherlands, a finding that is consistent with Adly (2006)[3]. Barassi et al. (2011) revisit the unit root properties of CO_2 emissions per capita for the period 1870 to 2004 by applying the ADF, NP and KPSS stationarity tests. Though their empirical results are found to be sensitive to the selection of the unit root test, the ADF and N-P unit root tests indicate that CO_2 emissions per capita possess a unit root problem. Subsequently, Christidou et al. (2013) examine the stationarity properties of CO_2 emissions per capita for a panel of 36 countries covering the period 1870 to 2006 by using Kapetanios et al. (2003)'s nonlinear panel unit root test, and they find that the per capita carbon dioxide emissions are stationary. Yavuz et al. (2013) test the stationarity properties of per capita carbon dioxide emissions emitted from gas, liquids, solids, cement production and gas flaring for the period 1960 to 2005 by using the threshold autoregressive (TAR) panel unit root test for G-7 countries. Their empirical analysis indicates that per capita carbon dioxide emissions are stationary in the first regime but exhibit a unit root problem in the second regime. This indicates that a regime shift is a cause of the non-stationarity of CO_2 emissions per capita. Li et al. (2014) employ the first generation panel unit root tests of Maddala and Wu (1999), Levin et al. (2002) and Im et al. (2003) and the second generation panel unit root tests of Choi (2002), Bai and Ng (2004), Moon and Perron (2004) and Pesaran 2007) in order to test the stationarity properties of CO_2 emissions using data for the 50 U.S. states. They also applied the KPSS unit root test developed by Kapetanios et al. (2003). Their analyses indicate that shocks to CO_2 emissions are transitory in 12 out of the 50 U.S. states, while

[3]Lee and Chang, (2009) also support that shocks to CO_2 emissions are transitory in Switzerland, as provided by the KPSS (Kwiatkowski et al. 1992) structural break unit root test.

shocks to CO_2 emissions are permanent in the remaining 38 states. Payne et al. (2014) re-examine the stochastic behaviour of sulphur dioxide (SO_2) emissions by applying the residual augmented least squares–Lagrange multiplier (RALS–LM) unit root test developed by Im et al. (2014), which accommodates structural breaks arising in the series. They document that shocks to CO_2 emissions are transitory, thus supporting the results reported by List (1999).

Recently, Hao et al. (2016) investigate the stochastic behaviour of carbon emissions intensity using provincial data for China by applying first generation panel unit root tests, i.e., IPS, ADF, PP and LLC panel unit root tests. Their results indicate a rejection of the null hypothesis, implying that the carbon emissions intensity is stationary. Barros et al. (2016) investigate the stationarity properties of carbon emissions emitted from gas, liquids, solids, cement production and gas flaring at the global level using the annual frequency data for the period 1751 to 2009. They find that shocks to carbon emissions are permanent. Gil-Alana et al. (2016) investigate the unit root behaviour of CO_2 emissions using data for G-7 and BRICS countries by applying the fractional integration test within a non-linear framework developed by Cuestas and Gil-Alana (2016). Their results indicate that shocks to CO_2 emissions have a permanent effect.

Thus, though various studies in the existing literature have investigated whether shocks to CO_2 emissions are transitory or permanent by applying different unit root tests, they have provided mixed empirical results. Accordingly, these empirical findings may not be helpful for policy makers because they give conflicting signals that could cloud the future distribution of CO_2 emissions. The unit root tests, such as ADF (Dickey and Fuller, 1981), PP (Philips and Perron, 1988), DF-GLS (Elliott et al. 1996) and N-P (Ng-Perron, 2001), were often applied to test the stationarity properties of CO_2 emissions per capita, but these unit root tests are not free of criticism. As indicated earlier, the original unit root tests failed to accommodate structural breaks embedded in the series due to economic policies. Although the KPSS (Kapetanios et al. 2003) and LM (Lee and Strazicich 2003, 2004) panel unit root tests accommodate structural breaks in the series, they have low explanatory power and over-reject the null hypothesis when it is true and vice versa (Barros et al. 2016). Similarly, the unit root tests, namely, the KPSS and LM, are suitable for small sample data, and the break magnitude changes with sample size (Narayan and Pop, 2010). With respect to the panel analyses, tests such as the MW (Maddala and Wu, 1999), the SURADF (Breuer et al. 2001), the IPS (Im et al. 2002), the LLC (Levin et al. 2002), the Choi (Choi, 2002), the BN (Bai and Ng, 2004), the MN (Moon and Perron, 2004), the TAR (threshold autoregressive) (Beyaert and Camacho, 2008), and the RALS–LM (residual augmented least squares–Lagrange multiplier) (Im et al. 2014) are employed for testing whether the unit root properties of CO_2 emissions are permanent or transitory. Yavuz and Yilanci (2013) argue that the MW, IPS, LLC, BN and MN unit root tests lack explanatory power and provide ambiguous results. Additionally, the TAR panel unit root accommodates two regimes, but the possibility of a third regime is ignored (Kapetanios and Shin 2006).

Structural breaks may occur in CO_2 emissions due to structural shifts in the economy, e.g., from agriculture to industry and then from industry to services. The presence of structural breaks may change CO_2 emissions modelling, testing and forecasting. The empirical evidence, without incorporating structural changes and regime shifts, results in an ambiguous and unreliable conclusion. However, the identification of structural changes may enable one to discover specific economic factors that caused CO_2 emissions to fluctuate significantly in low-, middle- and high-income countries over the sample period. Additionally, the implementation of environmental policies may be a cause of asymmetries in time series data, i.e., CO_2 emissions. The existing literature also indicates that ignoring the presence of asymmetries or non-linearity in macroeconomic variables may cause biased empirical results (Cuestas and Gil-Alana, 2016). However, the recent progress in the non-stationary panel unit root tests has shifted interest to include structural breaks in the panel data variables and cross-section dependence among the individuals of the panel[4]. These specifications are flexible enough to account for a large degree of heterogeneity.

In the current study, we employ new nonlinear unit root tests that account for nonlinear behaviour in the carbon emission series. We also apply panel unit root tests that allow for structural breaks and cross-section dependence, and we find that CO_2 emissions exhibit a stationary process.

[4]Jordá and Remuzgo (2014) also suggest considering nonlinearities while testing the unit root properties of CO_2 emissions to ensure a reliable empirical investigation.

3. Econometric methodology

3.1. Nonlinear unit root tests

We start by conducting the Harvey et al. (2008) linearity test, which tests the null hypothesis of linearity against the alternative of a nonlinear model. This test operates better in terms of size and power than the linearity test proposed by Harvey and Leybourne (2007). The motivation behind applying the linearity test is to determine whether CO_2 emissions per capita follow a nonlinear or linear path. If emissions per capita series follow a nonlinear path over time, the conventional linear unit root tests, i.e., ADF, PP, KPSS, etc., which suffer from power problems, tend to over accept the null hypothesis of linearity. An additional potential problem with the standard unit root tests is that these tests do not take into account the possibility of structural breaks in the time series variables. Subsequently, depending on whether one accepts or rejects the null hypothesis of the linearity of time series, we conduct unit root tests, such as the Lagrange multiplier (LM) unit root test with structural breaks (Lee and Strazicich, 2003, 2013). This test is applied if the time series exhibit linear behaviour, but we employ a nonlinear unit root test when the null of linearity is rejected. In order to perform a unit root test for the nonlinear series, we use the Kruse (2011) test, which is based on the exponential smooth transition autoregressive (ESTAR) unit root test suggested by Kapetanios et al. (2003) (KSS). Kruse suggests an extension of the KSS unit root test by allowing for a non-zero location parameter in the transition function to improve the size and the power of the KSS test. This test is built on the non-standard testing approach of Abadir and Distaso (2007), who introduce the modified Wald statistics for testing joint hypotheses when one of the alternatives is one-sided. In sum, the Kruse (2011) test is, as shown by the Monte Carlo study, more powerful than the existing test of Kapetanios et al. (2003).

3.2. Panel unit root tests without structural breaks

For the purpose of the robustness analysis, we perform the first generation panel unit root tests that assume the independence of cross-section panel units, and we then use the second generation panel tests that allow for cross-section dependence. The first generation panel tests that are conducted in this study include the Levin, Lin and Chu (2002) LLC test, the Im, Pesaran and Shin (2003) IPS test, the Maddala and Wu (1999) MW test and the Choi (2001) test. The second generation panel tests include the Moon and Perron (2004) MP test, the Pesaran (2007) test and the Choi (2002) CH test.

Tests	First Generation	Second Generation
Panel unit root tests	Levin, Lin and Chu (2002) LLC	Moon and Perron (2004)
	Im, Pesaran and Shin (2003) IPS	Pesaran (2007)
	Maddala and Wu (1999) MW	Choi (2002)

In order to test for the cross-section dependence in the panels[5], we use three tests, namely, the Pesaran (2004) cross-sectional dependence test, the Friedman (1937) statistic test and the test statistic proposed by Frees (1995). The cross-section dependence test depends on the average value of all pair-wise correlations of the OLS residuals associated with the individual regressions in the panel data model:

$$y_{it} = \alpha_i + \beta_i x_{it} + u_{it} \tag{1}$$

where $t = 1, \ldots, T$ denotes the time period, $i = 1, \ldots, N$ indexes the cross-section dimension and x_{it} is a k × 1 vector of the observed time-varying regressors, i.e., individual-specific as well as common regressors. The individual intercepts α_i and the slope coefficients β_i are defined on a compact set and allowed to vary across *i*. For each *i*, $u_{it} \sim iid(0, \sigma^2)$, for all t, and the cross-section dependence test statistic is defined as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \Rightarrow \mathrm{N}(0,1) \tag{2}$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals between *i* and *j*. Specifically,

[5]The cross-sectional dependence can arise due to an unobserved and/or omitted common factors, spatial correlations, economic distance and common unobserved shocks.

$$\hat{p}_{ij} = \hat{p}_{ji} = \frac{\sum_{t=1}^{T} \hat{\mu}_{it}\hat{\mu}_{jt}}{\left(\sum_{t=1}^{T} \hat{\mu}_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T} \hat{\mu}_{jt}^2\right)^{1/2}} \tag{3}$$

3.3. *Panel unit root tests with structural breaks*

This paper implements the panel KPSS test (Carrion-i-Silvestre et al. 2005), which allows for multiple structural breaks. The Bai and Carrion-i-Silvestre (2009) panel unit root test, which allows for both multiple structural breaks and cross-sectional dependence. The KPSS test is a generalization of Hadri (2000)'s panel stationarity test in the case of multiple changes in level and slope. The KPSS model contains three significant characteristics. First, it allows structural breaks to have different effects on each individual time series. Second, structural breaks may occur at different locations. Third, the individual series is allowed to have multiple structural breaks. This KPSS test is formulated as follows:

$$y_{iy} = \alpha_i + \sum_{k=1}^{m_i} \theta_{ik} DU_{ikt} + \beta_i t + \sum_{k=1}^{m_i} \gamma_{ik} DT_{ikt}^* + \varepsilon_{it} \tag{4}$$

where $i = 1, \ldots, N$ individuals and $t = 1, \ldots, T$ periods. The dummy variables $DT_{ikt}^*$and DU_{ikt} are defined as follows:

$$DT_{ikt}^* = \begin{cases} t - T_{bk}^i \text{ for} t > T_{bk}^i \\ 0 \quad \text{elsewhere} \end{cases}$$

$$DU_{ikt} = \begin{cases} 1 \quad \text{for} t > T_{bk}^i \\ 0 \quad \text{elsewhere} \end{cases}$$

whereT_{bk}^idesignates the *k*th date of the break for the *i*th individual series and $t = 1, \ldots, m_i$ for $m_i \geq 1$. This model contains shifts in the mean (individual effects) and in the trend (temporal structural breaks effects). Conversely, by applying the Hadri (2000) procedure, Carrion-i-Silvestre et al. (2005) compute the test's null hypothesis of a stationary panel as follows:

$$\eta(\hat{\lambda}) = \frac{1}{N}\sum_{i=1}^{N}\left(\omega_i^{-2}T^{-2}\sum_{t=1}^{T}\hat{S}_{it}^{2}\right) \tag{5}$$

where $\omega_i^{-2}T^{-2}\sum_{t=1}^{T}\hat{S}_{it}^{2} = \eta_i(\hat{\lambda}_i)$ is the univariate KPSS test for individual *i*, $\hat{S}_{it}^{2}$ is the partial sum of the estimated ordinary least squares residuals and ω_i^{-2} is a consistent estimator of the long-term variance (homogenous and/or heterogeneous) of ε_{it} based on the parametric method (Shin and Snell, 2006). This panel test is dependent on the positions of the dates of the breaks (λ_i) over the entire time *T* as follows:

$$\lambda_i = (\lambda_{i,1}, \lambda_{i,2}, \dots, \lambda_{i,m_i})' = (T_{b,1}/T, T_{b,2}/T, \dots, T_{b,m_i}/T)' \tag{6}$$

Carrion-i-Silvestre et al. (2005) determine these breaks endogenously by using the Bai and Perron (1998) procedure for each individual series. The appropriate number of breaks is selected by using the Bayesian information criterion (BIC) if the model includes trending regressors. After obtaining all parameters, the authors suggest using the following test statistic for the null hypothesis of a stationary panel with multiple breaks:

$$Z(\hat{\lambda}) = \frac{\sqrt{N}(\eta(\hat{\lambda}) - \bar{\xi})}{\bar{\varsigma}} \xrightarrow{d} N(0,1)$$

(7)

where $\xrightarrow{d}$ denotes weak convergence in distribution, and $\bar{\xi}$ and $\bar{\varsigma}^2$ are the average of individual means ($\bar{\xi}_i$) and variances ($\bar{\varsigma}_i^2$) of $\eta_i(\hat{\lambda}_i)$, respectively.

We also employ the panel unit root test proposed by Bai and Carrion-i-Silvestre (2009), which allows for both multiple structural breaks and cross-sectional dependence simultaneously through a common factors model proposed by Bai and Ng (2004). This test, which pools the modified Sargan and Bhargava (1983) tests for individual time series, takes into account a high degree of heterogeneity across units. Bai and Carrion-i-Silvestre (2009) extended the Bai and Ng (2004) panel unit root test to attain a robust decomposition into common and idiosyncratic components in the presence of structural breaks. This test is flexible enough to allow individual series to have breaks at different times and with different magnitudes. The panel unit root test is defined as follows:

$$y_{it} = \delta_i' D_{it} + \pi_i' F_t + e_{it} \tag{8}$$

$$(1 - L)F_t = C(L)u_t \tag{9}$$

$$(1 - \rho_i L)e_{it} - \Pi_i(L)\varepsilon_{it} \tag{10}$$

where $i = 1, \dots, N$ individuals and $t = 1, \dots, T$ periods. The dummy variables DT_{ikt} and DU_{jit} are defined as follows:

$$DT_{ikt} = \begin{cases} t & TB_k^i \text{for} t > TB_k^i \\ 0 & \text{elsewhere} \end{cases}$$

$$DU_{jit} = \begin{cases} 1 & \text{for} t > TB_k^j \\ 0 & \text{elsewhere} \end{cases}$$

for $j = 1, \dots, l_i$ and $k = 1, \dots, m_i$. F_t is an $(r \times 1)$ vector of common factors that measure the cross-sectional dependence, π_i is an $(r \times 1)$ vector of factor loadings, δ_i are the associated coefficients of the dummy variables and e_{it} is the error term. The differenced de-trended model is obtained using the principal components technique as follows:

$$y_i = F\pi_i + b_i\delta_i + w_i \tag{11}$$

where $y_i = (\Delta y_{i2}, \Delta y_{i3}, \dots, \Delta y_{iT})'$, $F = (\Delta F_2, \Delta F_3, \dots, \Delta F_T)'$ and $b_i = (b_{i2}, b_{i3}, \dots, b_{iT})'$ with $b_{it} = \left(1, D_{1,it}, \dots, D_{m_i,it}\right)$. The Bai and Carrion-i-Silvestre (2009) procedure consists of the following steps:

i. Find the difference of the variables, and estimate the number m_i as well as the locations of structural breaks for each time series;

ii. Estimate the common factors F_t, loadings factors π_i and the associated coefficients δ_i using an iterative procedure;

iii. Obtain the cumulative sum of residuals $\hat{e}_{it} = \sum_{s=1}^{t} \widehat{w}_{i,s}$, where $w_i = \hat{y}_i - \hat{F}\hat{\pi}_i - \hat{b}_i\hat{\delta}_i$ (the measured residuals for each time series);

iv. Employ the univariate modified Sargan-Bhargava (MSB) test proposed by Stock (1999), for each residual series. The test is defined as follows:

$$MSB_i(\lambda_i) = \frac{T - 2\sum_{t=1}^{T} \hat{e}_{i,t-1}^2}{\hat{\sigma}_i^2} \tag{12}$$

where $\lambda_{i,j} = TB_j^i / T$ and $\hat{\sigma}_i^2$ is a consistent estimator of the long-term variance $e_{it} - \rho_i e_{i,t-1}$.

v. Bai and Carrion-i-Silvestre (2009) constructed the panel MSB test by pooling the individual time series. They then use the average of the individual statistics as follows:

$$Z = \frac{\sqrt{N}\,(\overline{MSB(\lambda) - \bar{\xi}})}{\bar{\xi}} \rightarrow N(0,1) \tag{13}$$

where $MSB(\lambda) = \sum_{i=1}^{N} MSB_i(\lambda_i)/N$ and $\bar{\xi} = \sum_{i=1}^{N} \xi_i / N$.

Next, in order to calculate the Fisher-type test statistic, the authors use the same procedure applied by Maddala and Wu (1999) and Choi (2001) to pool the p-values associated with the individual tests as follows:

$$P = -2\sum_{i=1}^{N} \ln(p_i) \rightarrow \chi_{2N}^{N} \tag{14}$$

and

$$P_m = \frac{-2\sum_{i=1}^{N} \ln(p_i) - 2N}{\sqrt{4N}} \to N(0,1) \tag{15}$$

where p_i are the p-values associated with the individual MSB_i tests.

4. Data and empirical results

4.1. *Data*

To test the stationarity of the carbon dioxide emissions for 98 high-, middle- and low-income countries, we use annual data for total fossil fuel CO_2 emissions from 1975 to 2014. The categorization of countries into 35 high-income, 52 middle-income and 11 low-income economies is based on data derived from the World Bank (http://data.worldbank.org/news/new-country-classifications). We use the total population series to convert CO_2 emissions data into per capita units. All time series are in natural logarithms and have been obtained from the *World Development Indicator* database (World Bank).

4.2. Empirical results

We begin by conducting the Harvey et al. (2008) linearity test in order to determine whether the times series exhibit linear or nonlinear behaviour over time. Such a step allows one to decide whether to perform a linear or nonlinear unit root test. The results of the linearity test are displayed in Table 1. The hypothesis of linearity is rejected for 45% of the countries in our sample. This finding provides evidence that approximately half of the CO_2 emissions per capita are characterized by a nonlinear path over time. However, CO_2 emissions in the rest of the countries exhibit a linear path and when the LM unit root test with structural breaks is taken into account for these countries, the unit root null is rejected. Thus, in 55% of the countries, any shock to CO_2 emissions will have transitory effects because this variable will return to its trend path.

Since the linearity hypothesis is rejected for almost half of the countries, we conduct the nonlinear unit root test developed by Kruse, (2011) in order to examine the stationarity of nonlinear time series. The data in Table 2 reveal that 80% of the nonlinear series fail to reject the null hypothesis of the unit root. Thus any shock to CO_2 emissions is likely to be permanent, and as a consequence, the environmental policies will have a permanent impact on the following countries: Mexico, Argentina, Brazil, Chile, Venezuela, Bulgaria, Finland, France, Germany, Hungary, Ireland, Romania, India, Japan, Malaysia, South Korea, Tunisia, Qatar, Bolivia, Congo Dem. Rep., Gabon, Mozambique, Uruguay, Nigeria, Syria, Sweden, Turkey, Algeria, Libya, Sudan, Angola, Congo Rep., Cuba, Ghana, Haiti and Singapore.

Table 1: Linearity Unit Root Analysis

Countries	**Statistics**	**Prob. value**	**Result**	**Countries**	**Statistics**	**Prob. value**	**Result**
US	52.208	0.000	Nonlinear	Uruguay	13.809	0.008	Non linear
Canada	6.006	0.199	Linear	Spain	1.562	0.816	Linear
Mexico	8.545	0.074	Nonlinear	Sweden	11.083	0.026	Non linear
Argentina	9.485	0.050	Nonlinear	Switzerland	5.067	0.281	Linear
Brazil	11.588	0.021	Nonlinear	Turkey	10.914	0.028	Non linear
Chile	11.422	0.022	Nonlinear	Zambia	2.441	0.655	Linear
Colombia	14.640	0.006	Nonlinear	Iran	7.268	0.122	Linear
Ecuador	4.076	0.396	Linear	Algeria	11.010	0.026	Non linear
Peru	1.354	0.852	Linear	Egypt	6.222	0.183	Linear
Venezuela	14.258	0.007	Nonlinear	South Africa	5.236	0.264	Linear
Thailand	1.520	0.823	Linear	Australia	6.174	0.187	Linear
Bulgaria	19.361	0.001	Nonlinear	Bangladesh	5.177	0.270	Linear
Iraq	4.546	0.337	Linear	China	0.704	0.951	Linear
Finland	10.469	0.033	Nonlinear	India	10.032	0.040	Non linear
France	1.722	0.787	Nonlinear	Indonesia	0.954	0.917	Linear
Germany	26.329	0.000	Nonlinear	Japan	11.627	0.020	Non linear
Greece	6.581	0.160	Linear	Malaysia	11.933	0.018	Non linear
Hungary	11.734	0.019	Nonlinear	New Zealand	4.113	0.391	Linear
Ireland	17.463	0.002	Nonlinear	Pakistan	50.374	0.000	Non linear

Italy	0.000	1.000	Linear	Philippines	7.375	0.117	Linear
Norway	2.430	0.657	Linear	South Korea	11.181	0.025	Non linear
Poland	0.079	0.999	Linear	Tunisia	8.150	0.086	Non linear
Portugal	2.749	0.601	Linear	Qatar	7.908	0.095	Non linear
Romania	11.216	0.024	Nonlinear	Vietnam	2.854	0.583	Linear
UK	173.109	0.000	Nonlinear	Bahrain	2.764	0.598	Linear
Albania	3.236	0.519	Linear	Benin	5.427	0.246	Linear
Angola	29.933	0.000	Nonlinear	Bolivia	9.518	0.049	Non linear
Botswana	1.088	0.896	Linear	Cameroon	9.501	0.050	Non linear
Cote d'Ivoire	17.549	0.002	Nonlinear	Congo Dem. Rep.	15.440	0.004	Non linear
Congo Rep.	22.862	0.000	Nonlinear	Costa Rica	85.118	0.000	Non linear
Cuba	12.896	0.012	Nonlinear	Cyprus	6.728	0.151	Linear
Denmark	3.818	0.431	Linear	Dominican	4.304	0.366	Linear
Ethiopia	0.021	1.000	Linear	Gabon	9.351	0.053	Non linear
Ghana	9.712	0.046	Nonlinear	Guatemala	2.363	0.669	Linear
Haiti	15.844	0.003	Nonlinear	Honduras	0.261	0.992	Linear
Israel	2.128	0.712	Linear	Jamaica	3.793	0.435	Linear
Jordan	7.516	0.111	Linear	Kenya	3.064	0.547	Linear
Libya	15.055	0.005	Nonlinear	Kuwait	6.697	0.153	Linear
Malta	5.351	0.253	Linear	Morocco	6.928	0.140	Linear
Nepal	2.034	0.730	Linear	Mozambique	82.666	0.000	Non-linear
Netherland	5.294	0.258	Linear	Nicaragua	19.416	0.001	Non linear
Nigeria	20.272	0.000	Nonlinear	Oman	4.356	0.360	Linear
Panama	1.512	0.824	Linear	Paraguay	6.702	0.152	Linear
Salvador	5.276	0.260	Linear	Saudi Arabia	5.518	0.238	Linear
Senegal	5.031	0.284	Linear	Singapore	12.110	0.017	Non linear
Sri Lanka	1.827	0.768	Linear	Sudan	7.836	0.098	Non linear
Syria	11.509	0.021	Nonlinear	Tanzania	5.740	0.219	Linear
Togo	32.242	0.000	Nonlinear	Trinidad and Tobago	4.710	0.318	Linear
Zimbabwe	1.095	0.895	Linear	United Arab Emirates	1.296	0.862	Linear

Note: The 1%, 5%, and 10% critical values for the Harvey et al. (2008) test are 7.779, 9.488, and 13.277, respectively.

Table 2: ESTAR Unit Root Analysis

Countries	KSS	Result	Countries	KSS	Result
US	-12.385	Stationary	India	-2.222	Non-stationary
Mexico	-0.827	Non-stationary	Japan	-0.358	Non-stationary
Argentina	-0.136	Non-stationary	Malaysia	-1.635	Non-stationary
Brazil	-1.446	Non-stationary	Pakistan	-3.590	Stationary
Chile	-2.236	Non-stationary	South Korea	-1.151	Non-stationary
Colombia	-2.716	Stationary	Tunisia	1.994	Non-stationary
Venezuela	-1.254	Non-stationary	Qatar	-1.423	Non-stationary
Bulgaria	-1.920	Non-stationary	Bolivia	-1.748	Non-stationary
Finland	-2.127	Non-stationary	Cameroon	-3.005	Stationary
France	-1.665	Non-stationary	Congo Dem. Rep.	-1.263	Non-stationary
Germany	-0.676	Non stationary	Costa Rica	-67.624	Stationary
Hungary	-2.371	Non-stationary	Gabon	-0.487	Non-stationary
Ireland	-1.822	Non-stationary	Mozambique	-2.138	Non stationary
Romania	-2.214	Non-stationary	Nicaragua	-2.919	Stationary
UK	-6.342	Stationary	Singapore	-2.624	Non-stationary
Nigeria	-1.897	Non-stationary	Sudan	-0.649	Non-stationary
Syria	0.019	Non-stationary	Angola	-1.431	Non-stationary
Togo	-3.578	Stationary	Cote d'Ivoire	-4.554	Stationary
Sweden	-2.476	Non-stationary	Congo Rep.	-0.732	Non-stationary
Turkey	-1.996	Non-stationary	Cuba	-1.284	Non-stationary
Algeria	-1.744	Non-stationary	Ghana	-1.101	Non-stationary
Libya	-2.142	Non-stationary	Haiti	-2.537	Non-stationary
Uruguay	-2.586	Non-stationary	Iceland	-1.257	Non-stationary

Note: The exponential smooth transition autoregressive (ESTAR) unit root test. The 1%, 5%, and 10% levels for the critical values for the Kruse (2011) test are -3.48, -2.93, and -2.66, respectively.

We have applied the LM univariate linear unit root tests, without and with structural breaks, for time series that exhibit a linear path over time. We first applied the LM unit root tests that do not allow for structural breaks, i.e., Schmidt-Phillips (1992) test, and the results are available in Table 3. However, this test can lead to misleading inferences in time series testing because the test neglects the presence of structural breaks. The importance of allowing for the possibility of structural breaks when examining CO_2 emissions stationarity is confirmed by certain past events, e.g., the technological progress associated with the demand for higher energy density fuels and the regional wars between 1982 and 2009. Thus, we use a variety of the LM unit root tests taking into account one and two structural breaks in the levels and the trends. In the event of unknown breakpoint dates, models C and CC are more general and perform better than models A and AA, which allow for one and two structural breaks in the intercept. The results of all LM unit root tests are presented in Table 3. The unit root null hypothesis is rejected for 100% of the time series characterized by a linear path over time, highlighting that the environmental management policies designed to reduce the greenhouse gas emissions will have transitory effects as CO_2 emissions will return to their trend path.

Before performing the panel unit root tests, we conduct the cross-section dependence (CD) tests to check the presence of cross-sectional dependence and determine whether to apply the first or the second generation panel unit root tests. The results in Table 4 indicate that all tests of cross-sectional dependence reject the null hypothesis of no cross-sectional dependence. This finding highlights the importance of taking into account the cross-section dependence when examining CO_2 emissions stationary properties.

Table 3: LM Univariate Unit Root Analysis

	LM univariate test without breaks (Schmidt and Phillips, 1992)	k	LM univariate test with one break (Model C)	k	TB	LM univariate test with two breaks (Model CC)	k	TB_1	TB_2	Results
Canada	-0.0711 (-1.1107)	1	-0.6078*** (-4.2895)	3	2001	-0.7722*** (-5.0491)	3	1991	2001	Stationary with break
Ecuador	-0.0891 (-1.4143)	2	-0.4466 (-2.9583)	4	1993	-0.8798*** (-4.6664)	0	1989	2002	Stationary with break
Peru	-0.2196 (-1.5083)	0	-0.4044 (-3.0178)	4	1994	-0.9611*** (-4.8544)	0	1990	2003	Stationary with break
Thailand	-0.1705 (-1.8681)	4	-0.4476 (-3.1745)	4	1998	-0.8072** (-4.1387)	4	1983	1998	Stationary with break
Iraq	-0.2226 (-2.0732)	0	-0.9251 (-3.7511)	4	2001	-1.4264*** (-4.6135)	4	1984	2001	Stationary with break
Greece	-0.0692 (-0.7231)	0	-0.7125** (-4.0596)	0	2005	-1.1671*** (-5.5527)	1	1992	2005	Stationary with break
Italy	-0.0522 (-1.2348)	2	-0.6199*** (-6.2340)	3	2001	-0.5986*** (-7.3339)	3	1994	2001	Stationary with break
Norway	-0.2881 (-2.1154)	2	-0.6170** (-3.6377)	2	2002	-1.1908*** (-6.0960)	0	1991	2009	Stationary with break
Poland	-0.1572 (-1.6888)	0	-0.5968 (-3.1938)	1	1990	-1.0828*** (-5.3519)	1	1983	1999	Stationary with break
Portugal	-0.0753 (-1.3869)	1	-0.5713*** (-4.7713)	3	2002	-0.7563*** (-7.0090)	3	1992	2002	Stationary with break
Albania	-0.0279 (-0.3279)	0	-0.5660* (-3.2738)	0	1989	-1.1726*** (-5.5743)	1	1987	1997	Stationary with break
Botswana	-0.2795 (-1.9590)	3	-0.6664** (-3.8927)	0	1989	-0.9698*** (-5.0924)	0	1987	1993	Stationary with break
Denmark	-0.7686* (-3.0115)	3	-1.5391*** (-5.8872)	3	1990	-2.4156*** (-7.4811)	4	1990	2004	Stationary

Ethiopia	-0.5164** (-3.2279)	4	-0.4793** (-3.7703)	4	1998	-1.1645*** (-5.1325)	2	1994	2004	Stationary
Israel	-0.0773 (-1.1855)	0	-0.4908 (-2.8011)	0	1994	-2.8011*** (-4.5596)	0	1988	1995	Stationary with break
Jordan	-0.5362** (-3.2077)	3	-0.8785*** (-5.3179)	3	2003	0.8393*** (-6.2692)	1	1987	2003	Stationary
Malta	-0.2960 (-2.2273)	0	-0.9967*** (-5.3661)	0	1986	-1.1249*** (-5.8896)	0	1986	2009	Stationary with break
Nepal	-0.3374 (-2.6839)	0	-1.6916*** (-5.4280)	4	2006	-1.6364*** (-6.9043)	4	1994	2005	Stationary with break
Netherland	-0.4513*** (-3.6394)	2	-0.6719*** (-6.0472)	2	1992	-1.2908*** (-7.2480)	2	1984	1992	Stationary with break
Panama	-0.2311 (-2.0367)	2	-0.4663 (-3.1869)	2	1998	-0.8175** (-4.4580)	2	1987	2001	Stationary with break
Salvador	-0.3331 (-1.9050)	3	-0.9716*** (-4.8048)	0	1986	-1.8321*** (-7.5394)	1	1984	2003	Stationary with break
Senegal	-0.0584 (-0.6813)	0	-0.5013 (-3.1317)	2	1997	-1.9450*** (-6.2118)	3	1992	2004	Stationary with break
Sri Lanka	-0.1911 (-2.0121)	1	-0.4154 (-3.0924)	2	1993	-0.7898*** (-5.6065)	2	1989	2004	Stationary with break
Zimbabwe	-0.3163 (-2.5099)	3	-0.4839* (-3.4273)	3	1999	-0.8099*** (-4.8587)	3	1986	1999	Stationary with break
Spain	-0.2949 (-2.4453)	0	-0.8169*** (-4.3214)	2	1995	-1.2859*** (-4.8158)	4	1985	2002	Stationary with break
Switzerland	-0.1687 (-1.5886)	0	-0.6436** (-4.0276)	4	1998	-2.2396*** (-5.5696)	4	1983	2004	Stationary with break
Zambia	-0.1756 (-1.8091)	0	-0.7283* (-3.5151)	3	2006	-1.1939*** (-5.8008)	3	1984	2004	Stationary with break
Iran	-0.0428 (-1.1825)	1	-0.5275*** (-7.1290)	4	1999	-0.6923*** (-8.6749)	4	1992	2000	Stationary with break
Egypt	-0.0748 (-1.1451)	0	-0.6686 (-3.1815)	1	1996	-1.0687*** (-5.2495)	4	1993	2003	Stationary with break

South Africa	-0.1090 (-1.5392)	1	0.3813* (-3.4039)	3	1992	-1.2210*** (-4.8160)	3	1983	1995	Stationary with break
Australia	-0.2726 (-2.0253)	0	-1.7324*** (-5.5296)	4	1999	-1.9160*** (-6.0861)	4	1999	2003	Stationary with break
Bangladesh	-0.2054 (-1.6163)	0	-0.9451*** (-5.0505)	0	2000	-1.4909*** (-6.3342)	3	1992	2005	Stationary with break
China	-0.2119 (-1.6770)	0	-0.3534** (-3.5685)	1	1993	-1.1950*** (-5.1775)	3	1989	2004	Stationary with break
Indonesia	-0.2552 (-2.4985)	2	-0.1937 (-2.7053)	2	1996	-0.6563*** (-4.5878)	3	1988	2001	Stationary with break
New Zealand	-0.1410 (-2.2131)	2	-0.7215** (-4.0118)	4	2001	-1.1445*** (-4.9124)	4	1983	2004	Stationary with break
Philippines	-0.1320 (-1.4141)	0	-0.5046 (-2.9660)	4	2003	-1.1217*** (-5.8530)	4	1991	2004	Stationary with break
Vietnam	-0.3903 (-2.6384)	0	-0.6282* (-3.4478)	1	1986	-1.4873*** (-5.1427)	3	1984	2002	Stationary with break
Bahrain	-0.2918 (-2.1622)	0	-0.7145** (-4.0623)	0	1994	-1.2505*** (-4.8620)	2	1999	2005	Stationary with break
Benin	-0.0838 (-0.8911)	0	-1.1568*** (-4.9733)	3	2004	-1.7319*** (-7.8021)	4	1985	2004	Stationary with break
Cyprus	-0.0605 (-0.5792)	0	-0.4781** (-3.5914)	1	2003	0.7245** (-4.2894)	1	1990	2005	Stationary with break
Dominican	-0.6551*** (-3.8535)	0	-1.7316*** (-5.2005)	4	1985	1.9074*** (-6.1797)	4	1985	1992	Stationary with break
Guatemala	-0.2307 (-1.9566)	2	-0.8988** (-3.8072)	1	1991	0.8610*** (-5.0065)	1	1982	1991	Stationary with break
Honduras	-0.1113 (-1.3922)	0	-0.5635 (-3.1433)	0	2007	-1.7988*** (-6.2652)	4	1992	2004	Stationary with break
Jamaica	-0.0829 (-1.0040)	0	-0.8469*** (-5.1887)	1	1991	-1.1880*** (-8.2342)	1	1984	2000	Stationary with break

Kenya	0.1160 (-1.3293)	0	-0.5630* (-3.2893)	0	1986	1.0074*** (-5.0534)	0	1986	2001	Stationary with break
Kuwait	-0.3084 (-2.4398)	0	-0.9978*** (-5.3381)	0	1993	-1.9690*** (-7.8940)	4	1989	1993	Stationary with break
Morocco	0.1176 (-1.3895)	0	-0.6818*** (-4.3296)	4	1998	-0.8827*** (-5.2068)	4	1994	2005	Stationary with break
Oman	-0.1156 (-1.4071)	3	-0.6103** (-3.6933)	1	2000	-1.3537*** (-5.9381)	4	1986	2004	Stationary with break
Paraguay	-0.2636 (-2.3565)	0	-0.9863*** (-4.8312)	4	2004	-1.1743*** (-6.2335)	4	1987	2002	Stationary with break
Saudi Arabia	-0.1196 (-1.8772)	3	-0.5111** (-3.8650)	3	1994	-1.8017*** (-6.1002)	4	1986	2000	Stationary with break
Tanzania	0.0488 (-0.5798)	0	1.1737*** (-4.5317)	3	2003	0.8586*** (-7.5125)	3	1994	2003	Stationary with break
Trinidad and Tobago	-0.1056 (-2.4622)	3	-0.4064*** (-4.8449)	3	2000	0.9588*** (-8.4077)	4	1988	2002	Stationary with break
United Arab Emirates	-0.1907 (-1.8423)	0	1.1889*** (-4.7238)	4	1990	1.6191*** (-6.1602)	4	1987	2006	Stationary with break

Notes: Figures in the parentheses are t-values. The 1%, 5% and 10% critical values for the LM unit root test with no break are −3.63, −3.06, and −2.77, respectively. The 1%, 5%, and 10% critical values for the minimum LM test with one break are −4.239, −3.566, and −3.211, respectively. The 1%, 5%, and 10% critical values for the minimum LM test with two breaks are −4.545, −3.842, and −3.504, respectively. *, ** and *** represent significance at the 1%, 5% and 10% levels, respectively.

Table 4: Cross-sectional Dependence Test Analysis

Cross-sectional dependence test	Panel data form		
	High	Low	Middle
Frees' test of cross-sectional independence (p-values)	7.505 [0.000]	3.042 [0.000]	13.609 [0.000]
Pesaran's test of cross-sectional independence (p-values)	15.716 [0.000]	2.729 [0.006]	3.182 [0.001]
Friedman's test of cross-sectional independence (p-values)	160.266 [0.000]	56.265 [0.000]	56.990 [0.295]

As a starting point of the panel unit root tests, this study conducted the first generation panel unit root tests, which do not allow for both structural breaks and cross-sectional dependence. Levin et al. (2002) (LLC), Im et al. (2003) (IPS) and Maddala-Wu (1999) (MW) tests assume non-stationarity under the null hypothesis. As displayed in Table 5, the results suggest that CO_2 emissions per capita are integrated of order one, i.e., I(1). Hence, the first generation panel unit root tests fail to reject the null hypothesis of the unit root due to the omission of cross-section dependence and structural break hypotheses. Therefore, the consideration of these two assumptions may provide more consistent results.

Consequently, as a second step, we apply the second generation panel unit root tests which take into account the cross sectional dependence hypothesis. The results, as presented in Table 5, provide evidence of stationarity for all the second generation tests (Moon-Perron 2004, Choi 2002) except for the Pesaran (2007) unit root test. The failure to take into account the presence of structural breaks can provide inconclusive empirical results (Perron, 1989). This is also true for the panel tests since panel data include the time series dimension mentioned by Lee and Chiu (2011). For that reason, in the last step, we use the panel unit root tests with structural breaks (Carrion-i-Silvestre et al. 2005).

Following Bai and Perron (2001), we estimate the number of structural breaks associated with each country using the modified Schwarz information criterion (Liu, Wu and Zidek - LWZ) of Liu et al. (1997). The empirical analysis first specifies a maximum of $m^{\max} = 5$ structural breaks. We compute the finite sample critical values by means of the Monte Carlo simulations using 10,000 replications in order to reduce the bias and increase the power of the tests.

Table 5: Panel Unit Root Analysis

First Generation Panel Unit Root Tests: High-income panel				
Types of test statistic	**Test statistic**	**1% CV**	**5% CV**	**10% CV**
LLC test statistic	-1.1012	-2.3263	-1.6449	-1.2816
IPS test statistic	-1.1114	-2.3263	-1.6449	-1.2816
MW test statistic	57.1120	100.4252	90.5312	85.5270
Second-generation panel unit root tests: High-income panel				
Moon Perron1 statistic (ta_bar statistic)	-6.2548***	-2.3263	-1.6449	-1.2816
Moon Perron2 statistic (tb_bar statistic)	-5.4746***	-2.3263	-1.6449	-1.2816
Pesaran test, (2007)	-1.8584	-2.8075	-2.6593	-2.5850
Choi test statistic (P_m)	4.7825***	2.3263	1.6449	1.2816
Choi test statistic (Z)	-3.0689***	-2.3263	-1.6449	-1.2816
Choi test statistic (Lstar)	-3.2049***	-2.3263	-1.6449	-1.2816
First Generation of Panel Unit Root Tests: Low-income panel				
LLC test statistic	3.9122	-2.3263	-1.6449	-1.2816
IPS test statistic	1.0763	-2.3263	-1.6449	-1.2816
MW test statistic	16.2817	40.2894	33.9244	30.8133
Second-generation panel unit root tests: Low-income panel				
Moon Perron1 statistic (ta_bar statistic)	-1.3079*	-2.3263	-1.6449	-1.2816
Moon Perron2 statistic (tb_bar statistic)	-1.3099*	-2.3263	-1.6449	-1.2816
Pesaran test, (2007)	-1.3000	-3.1119	-2.8568	-2.7308
Choi test statistic (P_m)	-0.5468	2.3263	1.6449	1.2816
Choi test statistic (Z)	2.0868	-2.3263	-1.6449	-1.2816
Choi test statistic (Lstar)	2.5228	-2.3263	-1.6449	-1.2816
First Generation Panel Unit Root Tests: Middle-income panel				
LLC test statistic	-1.1184	-2.3263	-1.6449	-1.2816
IPS test statistic	-1.0094	-2.3263	-1.6449	-1.2816
MW test statistic	121.1120	142.7804	131.0315	125.0354
Second-generation panel unit root tests: Middle-income panel				
Moon Perron1 statistic (ta_bar statistic)	-5.2045***	-2.3263	-1.6449	-1.2816

Moon Perron2 statistic (tb_bar statistic)	-5.2017***	-2.3263	-1.6449	-1.2816
Pesaran test, (2007)	-2.1675	-2.9330	-2.7534	-2.6676
Choi test statistic (P_m)	-1.1020	2.3263	1.6449	1.2816
Choi test statistic (Z)	3.1769	-2.3263	-1.6449	-1.2816
Choi test statistic (Lstar)	4.1043	-2.3263	-1.6449	-1.2816

Notes: The first and second columns denote the panel unit root tests and the associated statics, respectively. The three last columns present the critical values of each panel unit root test at the 10%, 5%, and 1% levels. *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively. CV denotes the critical value.

Table 6: Multiple Structural Break Unit Root Analysis

High-Income Panel			
	Bartlett	Bootstrap critical values	
	Test (p-value)	10%	5%
No breaks (homogeneous)	16.755*	10.764	16.713
No breaks (heterogeneous)	20.497*	10.683	15.176
Breaks (homogeneous)	0.261	-2.761	-3.175
Breaks (heterogeneous)	8.123*	4.371	7.301
	Quadratic	Bootstrap critical values	
	Test (p-value)	10%	5%
No breaks (homogeneous)	18.355*	11.613	16.596
No breaks (heterogeneous)	21.087*	11.642	16.363
Breaks (homogeneous)	0.258	4.423	6.562
Breaks (heterogeneous)	8.057*	4.735	8.389
Middle-Income panel			
	Bartlett	Bootstrap critical values	
	Test (p-value)	10%	5%
No breaks (homogeneous)	15.781*	8.682	13.286
No breaks (heterogeneous)	21.183*	10.153	15.489
Breaks (homogeneous)	0.541	4.629	6.566
Breaks (heterogeneous)	3.751*	4.907	6.996
	Quadratic	Bootstrap critical values	
	Test (p-value)	10%	5%
No breaks (homogeneous)	15.873*	8.609	13.595
No breaks (heterogeneous)	21.653*	10.283	16.578
Breaks (homogeneous)	0.702	4.523	6.608
Breaks (heterogeneous)	3.743*	4.781	6.841
Low-Income Panel			
	Bartlett	Bootstrap critical values	
	Test (p-value)	10%	5%
No breaks (homogeneous)	8.543*	4.437	7.794

No breaks (heterogeneous)	10.438*	5.089	9.015
Breaks (homogeneous)	0.311	3.500	5.114
Breaks (heterogeneous)	2.648*	3.770	5.965
	Quadratic	Bootstrap critical values	
	Test (p-value)	10%	5%
No breaks (homogeneous)	9.092*	5.605	9.568
No breaks (heterogeneous)	11.334*	6.120	10.264
Breaks (homogeneous)	0.333	3.356	5.151
Breaks (heterogeneous)	2.863*	3.879	5.918

Notes: The number of break points has been estimated using the modified Schwarz information criteria allowing for a maximum of 5 structural breaks in the intercept and the trend. The long-term variance is estimated using both the Bartlett and the quadratic spectral kernel with an automatic spectral window bandwidth selection as in Andrews (1991), Andrews and Monahan (1992) and Sul et al. (2003). Significance is determined using the bootstrap critical values based on a Monte Carlo simulation with 10,000 replications. * represents significance at 1% level.

When we employ the Carrion-i-Silvestre et al. (2005) panel stationary test with multiple structural breaks, we find that this test provides strong support for stationarity of per capita CO_2 emissions for the three country panels, namely, high-income countries, middle-income countries and low-income countries, once the levels and/or the slope shifts are taken into account (see Table 6). However, when we allow for possible structural breaks, we strongly reject the unit root hypothesis for both homogeneous and heterogeneous long-term variance for all of the panels. The salient policy implication that emerges from these results is that any shocks to per capita CO_2 emissions are likely to be transitory and that environmental policies are not urgent as per capita CO_2 emissions will return to their trend path.

Table 7: Panel Unit Root Analysis with Structural Breaks and Cross-Sectional Dependence

Model	**Test**	**High-income**	**Middle-income**	**Low-income**
Constant and trend	Z	-1.137	-1.232	-0.763
	P	34.362	39.482	31.767
	P_m	0.672	0.947	0.512
Mean shift	Z	-1.351*	-2.367***	-1.298*
	P	47.827**	62.592***	43.56*

	P_m	1.291*	2.354***	1.287*
Trend shift	Z	-1.794**	-2.438***	-1.311*
	P	50.959***	67.864***	48.711**
	P_m	1.825**	2.504***	1.442*

Notes: *Z*, *P* and *Pm* denote the test statistics developed by Bai and Carrion-i-Silvestre (2009). The 1%, 5% and 10% critical values are as follows: a) for the standard normal distributed *Z,* they are equal to -2.326, -1.645 and -1.282, respectively; b) for the chi-squared distributed *Pm* statistics, they are 2.326, 1.645 and 1.282, respectively; and c) for the *P* statistic, they are 50.89, 46.98 and 40.25, respectively. The number of common factors is estimated using the panel Bayesian information criterion proposed by Bai and Ng (2002). *, ** and *** denote significance at the 10%, 5%, and 1% levels, respectively.

For conducting a robustness check, we applied Bai and Carrion-i-Silvestre (2009) panel unit root tests, which allow for multiple structural breaks and cross-sectional dependence. As displayed in Table 7, the null hypothesis of the unit root is strongly rejected for all three panels. The Carrion-i-Silvestre (2005) panel unit root KPSS test also suggests that CO_2 emissions per capita contain stationarity.

5. Conclusion and Policy Implications

This study investigates the stationarity properties of CO_2 emissions per capita for 98 low-, middle- and high-income countries over the period from 1975 to 2014. In the first step, we perform the individual nonlinear unit root test when the time series exhibit a nonlinear behaviour over time. Thus, the novel methodology of Kruse (2011) is used, and in the second step, we conduct the panel unit root tests, which allow for both structural breaks and cross-section dependence. The overwhelming evidence from the empirical findings favours non-stationarity, which is probably due to a lack of power of the first generation panel unit root tests.

Our contribution to the empirical literature is twofold. First, we investigate the linearity property in the underlying series by employing the Harvey et al. (2008) linearity test. This step allows one to decide whether the linear or the nonlinear unit root tests should be applied. In fact, if the emissions per capita series follow a nonlinear path over time, then the standard linear unit root tests (ADF, PP, KPSS, etc.) suffer from power problems and do not take into account the possibility of structural changes. Second, we apply the panel unit root tests that allow simultaneously for the existence of structural breaks and cross-sectional dependence in order to capture the true data generating process of CO_2 emissions per capita. The economic and energy events are likely to cause structural breaks, thus, the existence of strong inter-economic linkages between countries cannot reasonably be ignored.

The main empirical result in this paper suggests that approximately half of the CO_2 emissions series are characterized by a nonlinear path over time, and the unit root null is rejected for less than 60% of the countries. First, the finding implies that shocks will only have transitory effects for these countries, and this, in turn, makes CO_2 emissions per capita a mean-reverting process. However, for the remaining countries of the sample, the shocks to carbon dioxide emissions would have permanent effects, indicating that environmental policy interventions are highly recommended for these countries[6] given that 90 per cent are high- and middle-income countries.

Consequently, some policy implications arise from the empirical findings. In the context of the new Paris agreement on climate change (December, 2015), 195 countries agreed, by consensus, to reduce, as soon as possible, their greenhouse gas emissions in order to keep global warming well below 2 degrees Celsius above pre-industrial levels. First, a policy recommendation to accomplish this target is to provide support of worldwide access to sustainable energy in developing countries through the enhanced deployment of renewable energy.

Second, the process in the unit root tests confirms that time series are produced by nonlinear behaviour, thus, it is essential to allow for nonlinear properties for modelling and forecasting. Therefore, in order to search for more concrete evidence, we investigate the nonlinear dynamic proprieties of CO_2 emissions per capita and find that 40% of the series are non-constant over time. The nonlinearity of CO_2 emissions per capita is caused by many factors including different energy shocks, climate change, economic downturns, industrialization processes, differences in regulatory policies, etc. The contribution of this

[6]Mexico, Argentina, Brazil, Chile, Venezuela, Bulgaria, Finland, France, Germany, Hungary, Ireland, Romania, India, Japan, Malaysia, South Korea, Tunisia, Qatar, Bolivia, Congo Dem. Rep., Gabon, Mozambique, Uruguay, Nigeria, Syria, Sweden, Turkey, Algeria, Libya, Sudan, Angola, Congo Rep., Cuba, Ghana, Haiti and Singapore.

paper is that it makes a distinction between the nonlinear behaviour of emissions series and structural breaks, thus helping us to understand the difference among the countries under consideration, and it sheds light on the degree of heterogeneous chronological evolution of each series.

Third, our empirical findings provide evidence of structural breaks in CO_2 emissions per capita that occur between 1982 and 2009. During this period, the structural breaks in the carbon dioxide series may refer to rapid economic growth in some economies, such as the Asian emerging countries. By the early 21st century, CO_2 emissions from the middle-income countries exceeded those of the high-income countries. The result in our sample suggests that 50 per cent of the middle-income countries provide evidence of I(1) CO_2 emissions per capita, thus a stronger policy intervention is recommended given the permanent effects of the shocks in CO_2 emissions in these countries. However, CO_2 emissions per capita are found to be stationary for 65% of the high-income countries.

Finally, the result of the panel unit root tests change considerably when we allow for structural breaks and cross-sectional dependence between countries. These two features provide important test power gains compared to the first generation panel unit root tests. We find that stationarity of per capita CO_2 emissions cannot be rejected for any of the three country panels, i.e., high-, middle- and low-income countries. The worldwide emissions reduction policy is likely to support the process of abatement. Any incentives or policy measures that enable developing countries to substitute technologies involving lower emissions would contribute further in this regard. Accordingly, regional and international cooperation to mobilize stronger and more ambitious climate action would assist emissions abatement.

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