Environmental Degradation, Economic Growth and Non-renewable Energy in Selected South Asian Countries: Trivariate Analysis From DCCE-MG Approach

Bosede Ngozi ADELEYE (ngozi.adeleye@covenantuniversity.edu.ng)
Covenant University https://orcid.org/0000-0002-1274-714X

Darlington AKAM
University of Lagos

Nasiru INUWA
Gombe State University

Henry Tumba JAMES
Adamawa State University

Denis BASILA
Adamawa State University

Evans OSABUOHIEN
Covenant University

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Abstract

This study investigates and provides evidence on the impact of economic growth and non-renewable energy on environmental degradation. Using unbalanced panel data from 1990 to 2018 on five South Asian countries and engaging the dynamic common correlated effects-mean group (DCCE-MG) technique of Ditzen (2016, 2018), findings support the energy-led degradation hypothesis while the growth-led degradation hypothesis does not hold but both are supported from FMOLS and DOLS robustness checks. In order words, non-renewable energy and economic growth significantly drive environmental degradation. Country-level results are mixed with Nepal evidencing energy-led degradation, Pakistan shows growth-led degradation while India indicates growth-led sustainability. Supportively, the Dumitrescu-Hurlin (2012) non-Granger causality test establishes: (1) energy-led and growth-led degradation, (2) feedback causal relation between environmental degradation and non-renewable energy, and (3) unidirectional causality from growth to non-renewable energy i.e. "conservation" hypothesis. Policy implications are discussed.

Keywords: growth-led degradation, energy-led degradation, environmental degradation, South Asia

1 Introduction

The drive to maintain a sustainable environment necessitated the 2030 United Nations Sustainable Development Goal (SDG) 13 agenda, which is to *"take urgent action to combat climate change and its impacts"*. Therefore, to address climate change, it becomes imperative to understand its contributing factors: one of which is carbon dioxide (CO_2) emissions. The sources of carbon emissions are mainly from the burning of fossil fuel in a productive system with active power generation, transport, residential and industrial sectors (IPCC, 2018). These type of carbon emissions are known as "greenhouse" gases which should have been absorbed by space but are trapped by absorbing solar energy thereby heating the earth to cause global warming (National Geographic, 2019). This trapping of heat is known as the "greenhouse effect" which exemplifies environmental degradation.

Two key facts emanate from the illustrated scenario. First, the burning of fossil fuel evidences the usage of non-renewable energy which are divided into four components: coal, natural gas, oil, and nuclear energy. This combination not only alters the earth's atmosphere but also emit varieties of pollutants that negatively affect human health (IPCC, 2018). Secondly, the burning of fossil fuel typifies an active, vibrant and growing economy. In other words, non-renewable energy and economic growth are the identified drivers of environmental degradation, proxied by carbon emissions (Afridi, Kehelwalatenna, Naseem, & Tahir, 2019; Dogan & Aslan, 2017; Magazzino, 2016a; Murshed & Dao, 2020; Nathaniel, Barua, Hussain, & Adeleye, 2020; Osabuohien, Efobi, & Gitau, 2014; Parker & Bhatti, 2020; Shahbaz & Sinha, 2018; Urhie, Afolabi, Afolabi, Matthew, Osabohien, Ewetan, & Amoo, 2020). Hence, with the danger posed by increasing emissions, most developing economies are primarily saddled with the seemingly impossible task of curbing emissions amidst achieving steady economic growth and unhindered energy supply. The enormous threat posed by environmental degradation and the quest for economic growth and development, have further complicated the economic and environmental sustainability drive of developing economies, like those in South Asia. Given that environmental threat is heightened by the surge in global emissions and warming (IPCC, 2018), which pose an enormous danger to humans, marine life and the terrestrial ecosystem serves as the motivation for the examination of environmental degradation within a trivariate framework.

This study positions on South Asia which comprises of eight (8) countries: Afghanistan, Bangladesh, Bhutan, India, Nepal, The Maldives, Pakistan, and Sri Lanka based on three

reasons: (1) pollution, (2) economic growth, and (3) energy demand. Firstly, according to IQAir (2019), South Asia is the most polluted region, with 27 of the 30 most polluted cities located therein. India inhabits 21 of those cities. For $PM_{2.5}$[1] using a weighted population average, Bangladesh emerges as the most polluted country followed by Pakistan, Mongolia, Afghanistan and India with deviations of less than 10% from one another. Among others, the surge in air pollution has adversely affected human health and tourist inflows with negative revenue and socio-economic shocks and spill-overs (TERI, 2019). Second, World Bank (2019a, 2019b) positioned the region as the fastest-growing region in the world though growth moderated from 7.2 percent in 2017 to 6.9 percent in 2018. Also, the countries have divergent economic outlooks which make comparativeness intrinsic. From United Nations (2019), in contrast to Pakistan, the economic conditions in Bangladesh, Bhutan and India are mostly positive with positive GDP growth projections. Lastly, energy demand is higher in Asia and projected to double between 2018 and 2050, making it both the largest and fastest-growing region in the world for energy consumption (EIA, 2019). Besides, India is one of the world's fastest-growing economies during much of the past decade, and they remain primary contributors to future growth in world energy demand (IEA, 2019a, 2019b).

The purpose of this study is to contribute to the empirical debate on whether economic growth and non-renewable energy demand trigger environmental degradation through the emissions of carbon dioxide in South Asia. To achieve this, an unbalanced panel data of per capita GDP (a proxy for economic growth), non-renewable energy per capita and carbon emissions per capita from five selected South Asian[2] countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka) spanning 1990 to 2018 is used to: (1) investigate the growth-led and energy-led degradation relation; (2) assess if the growth-led and energy-led degradation relation significantly differ across the countries; and (3) establish the direction of causality among the variables. Similar to Shahbaz, Jam, Bibi, and Loganathan (2016), this paper further differs from previous studies on SAARC or South Asian countries (see Sharma, Kishan, and Doig (2014), Uddin and Wadud (2014), Pandey and Mishra (2015), Osmani (2018), Rahman, Saidi, and Mbarek (2020)) by strictly engaging a dynamic trivariate model to analyse the relationship. The possible endogeneity and dynamic nature of carbon emissions necessitate the need to employ a dynamic modelling approach. In other words, a dynamic model best captures the

[1]Fine particulate matter.
[2]Afghanistan, Bhutan, Maldives are dropped due to lack of sufficient data points.

behaviour of an outcome which changes as a result of its past realisations. Hence, the study conjectures that carbon emissions respond to its past level(s), and the indicators of non-renewable energy and per capita income. Given this, Ditzen (2016, 2018) dynamic common correlated effects-mean group (DCCE-MG[3]) approach which is an improvement on Chudik and Pesaran (2015) common correlated effects-mean group (CCE-MG) procedure is employed to address the first objective. This technique is justified because: (1) there is a possibility of cross-sectional dependence among the South Asian countries; (2) this study uses an unbalanced panel data; (3) carbon emissions is dynamic as the past levels are expected to influence future behaviours. Hereafter, the lagged dependent variable is included as a regressor; and (4) homogenous assumption of the slope coefficients since South Asian countries have some level of commonness such as common trade terms, monetary policies, and technologies. The DCCE-pooled mean group (DCCE-PMG) technique is engaged for the second objective while for the third objective, the Dumitrescu-Hurlin (2012) Granger non-causality procedure is employed to determine the direction of causation between the variables. Lastly, for robustness, the dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) techniques are deployed to ascertain if the results obtained via the DCCE-MG technique hold. The rest of the paper is structured as follows: section 2 reviews the empirical literature; section 3 outlines the data and empirical model; section 4 discusses the results, and section 5 concludes with policy recommendations.

2 Review of Extant Literature

Carbon emission is the proxy for environmental degradation, and the pursuit for a sustainable environment led to investigations on the drivers of carbon emissions. Several studies which will be highlighted in this section have explored different factors that aggravate environmental degradation with diverse outcomes partly due to the scope under coverage, the analytical technique and the choice of control variables. Therefore, without claim to being exhaustive, the carbon emissions literature is reviewed along with time series and panel data frameworks.

2.1 Time series outcomes

Covering the period 2005 to 2016, Ma, Wang, Dong, Gu, Chen, Li, and Li (2019) use a non-parametric procedure on the relation between carbon emissions and energy consumption to

[3]The Ditzen (2018) procedure also accommodates the pooled mean group variant for long-run homogenous slope coefficients. This assumption is invoked for the country-level analysis.

conclude that economic growth is the primary predictor of carbon emissions in China. Analogous to Lin and Raza (2019) who find that energy intensity reduces carbon emissions in Pakistan for the period 1978 to 2017. Likewise, Shaheen, Sheng, Arshad, Salam, and Hafeez (2019) use the ARDL technique to show that in the long run, energy consumption and gross domestic product (GDP) intensify carbon emissions in Pakistan from 1972-2014. Salahuddin, Gowb, Ali, Hossain, Al-Azami, Akbar, and Ayfer (2019) use Zivot-Andrews breakpoint analysis to conclude that urbanisation and globalisation are the drivers of emissions in South Africa from 1980 to 2017. Similarly, Wang, Wang, Li, Fang, and Feng (2019) on China from 1995 to 2014 use the ridge analysis to reveal that population, urbanisation and industrialisation fuel carbon emissions. From 1970 to 2017, Sarkodie and Strezov (2018) deploy the dynamic autoregressive distributed lag (ARDL) model to reveal that energy consumption is a positive predictor of carbon emissions in Australia.

On Iran from 2002 to 2013 and using the dynamic ordinary least squares (DOLS) and vector error correction model (VECM) procedures, Shabani and Shahnazi (2019) conclude that growth, energy use and information technology are the drivers of carbon emissions. Also, Li, Zhou, and Wang (2019) use the fixed and random effects models to conclude that urbanisation, agro-tech and information technology are the major drivers of carbon emissions. On the study of Saudi Arabia from 1990 to 2015, Omri, Euchi, Hasaballah, and Al-Tit (2019) use the fully modified ordinary least squares (FMOLS) and DOLS to conclude that trade openness, financial development and foreign direct investment (FDI) are the principal contributors of carbon emissions. Similar to Okoye, Omankhanlen, Okoh, Adeleye, N., K., and Ehikioya (2021), Yang, Zhang, Xue, Ma, Chen, and Lu (2018) use the ARDL technique to find that trade openness and urbanisation drive emissions in China from 1995 to 2014. Sarkodie and Strezov (2018) conclude using FMOLS and DOLS that renewable energy stalls emissions in Australia from 1974 to 2013. Shahbaz, Shahzad, and Mahalik (2018) also use the ARDL approach to find that globalisation, energy use and economic growth exacerbate emissions in Japan from 1970 to 2014.

On Kuwait, Salahuddin, Alam, Ozturk, and Sohag (2018) deploy the ARDL, VECM, and DOLS techniques to find that the principal determinants of carbon emissions from 1980 to 2013 are FDI, energy use and economic growth. Likewise, Khan, Saleem, and Fatima (2018) deploy the FMOLS technique to find that financial development reduces emissions in India, Bangladesh, and Pakistan from 1980 to 2014. Zhou, Fu, Kong, and Wu (2018) find that FDI

induces more carbon emissions in China from 2003 to 2015 using the ARDL technique. Roy, Basu, and Pal (2017) deploy the ridge technique on India from 1990 to 2016 and conclude that energy use reduces carbon emissions. Mirza and Kanwal (2017) from the VECM and ARDL procedures find a feedback relation between emissions/growth and emissions/energy use in Pakistan from 1979 to 2009. However, Bukhari and Waseem (2017) find a one-way causal impact from energy use to emission in Pakistan from 1972 to 2013 using the ARDL approach.

2.2 Panel Data Outcomes

Eurostat (2020) from the study of 27 member countries finds that carbon emission is a major contributor to global warming and account for some 80% of all human-made European Union (EU) greenhouse gas emissions. Shahbaz, Mahalik, Shahzad, and Hammoudeh (2019) deployed cross-correlation techniques to find that globalisation reduces carbon emissions from the study of 87 countries from 1970 to 2012. The study validates the existence of the pollution haven hypothesis (PHH), for the FDI/emissions and growth/emissions relations. Neagu and Teodoru (2019) use the DOLS and FMOLS procedures to show that a long-term equilibrium relationship exists among growth, energy use and greenhouse gas (GHG) emissions in 25 EU countries. Churchill, Inekwe, Smyth, and Zhang (2019) on the study of G7 countries from 1870 to 2014, use a non-parametric approach to show that emissions and research and development exhibit time-varying features. Nguyen and Kakinaka (2019) deployed panel cointegration techniques in 107 countries from 1990 to 2013 to show that renewable energy stall carbon emissions in high-income countries. Correspondingly, Shahbaz, Balsalobre-Lorente, and Sinha (2019) use the generalised method of moments (GMM) technique to examine the association between FDI and carbon emissions for the Middle East and North African (MENA) region in 1990–2015.

From the analysis of high, middle, and lower-income countries, Azizalrahman (2019) use the ARDL procedure to find that urbanisation and energy consumption are the drivers of carbon emissions in high-income countries from 1973 to 2013. Using the quantile-on-quantile technique, Mallick, Padhan, and Mahalik (2019) find that the poor do not contribute to carbon emissions in the case of BRICS member-states from 1980 to 2014. Alike, Inglesi-Lotz (2018) use a non-parametric procedure on the study of BRICS member-states from 1990 to 2014 and finds that carbon emission is reduced with changes in energy and carbon intensity. This outcome is similar to Mahalik, Mallick, Padhan, and Sahoo (2018) who find that, except for Brazil, coal consumption drives carbon emission in BRICS member-states from 1980 to 2013.

Equally, using a non-parametric approach, Chang, Dong, Sui, and Chu (2019) on analysing 121 countries show that population surge, energy consumption, economic growth and carbon intensity are the principal drivers of emissions from 2000 to 2014. Acheampong (2018) deploys the GMM and panel vector autoregressive (PVAR) techniques on a study of 116 countries from 1990 to 2014 to show that feedback causal relation exists between emissions/growth and emissions/energy use. Also, on a study of 17 countries from 1971 to 2013, Sarkodie (2018) deployed the fixed and random effects techniques to show that both globalisation and energy usage Granger-cause carbon emissions. On the study of 13 Asian countries from 1980 to 2010, Salim, Rafiq, and Shafiei (2017) deploy the augmented mean group (AMG) approach to show that trade liberalisation, urbanisation and renewable energy consumption reduce carbon emissions.

3 Data and Model

3.1 Data

This study employs an unbalanced annual panel data of selected five South Asian countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka) from 1990 to 2018. These countries are chosen subject to data availability. The dependent variable is carbon emissions *(CO_2)* measured in metric tons per capita. It is the proxy for environmental degradation (Alvarez-Herranz, Balsalobre-Lorente, Shahbaz, & Cantos, 2017; Anatasia, 2015; Cetin & Ecevit, 2017; Lorente & A., 2016; Nathaniel & Adeleye, 2021; Shahbaz, Lean , & Shabbir, 2012). The independent variables are gross domestic product per capita *(PC)* at constant 2010 US$, and energy use *(ENU)* measured as kg of oil equivalent per capita. All variables are sourced from World Bank (2019c) World Development Indicators database. The variable names, codes, sources, *a priori* expectations, descriptive statistics and correlation analysis are presented in Tables 1 and 2.

Table 1 Variables, Code, Source, and Expectations

Variables	Code	Source	Expectations
Carbon emissions capita	CO_2	World Bank (2019) WDI	N/A
GDP per capita	*PC*	-do-	Positive
Energy use per capita	*ENU*	-do-	Positive

Note: *WDI* = World Development Indicators; *N/A* = Not Applicable
Source: Authors' Compilation

From the outcomes shown in Table 3, the maximum CO_2 emissions per capita is 1.724 emitted by India in 2014, while the lowest of 0.034 is traced to Nepal in 1990. With the mean value of 0.560, the standard deviation of 0.385 does not suggest wide dispersion from the mean by

countries in the sample. Similarly, per capita GDP has a mean score of US$1,106.092 with minimum and maximum values of US$3,936.45 and US$354.258 from Sri Lanka in 2018 and Nepal in 1990, respectively. The standard deviation of 785,045 indicates wide dispersion from the sample mean. On average, non-renewable energy use per capita has a mean score of 366.577and a variability of 122.44. The maximum value of 636.57 is traced to India in 2014 while the lowest of 118.898 is from Bangladesh in 1991. Deductively, India's rising CO_2 emissions is in tandem with the country's rate of non-renewable energy consumption. On the shape of the distribution, per capita GDP and CO_2 exhibit positive skewness and kurtosis, while non-renewable energy consumption exhibits negative skewness but positive kurtosis suggesting a spike in the energy consumption of these countries.

Table 2 Descriptive Statistics and Correlation Matrix

Variable	CO_2 Emissions	per capita GDP	Energy Use per capita
	Panel A: Descriptive Statistics		
Mean	0.560	1106.092	366.577
Maximum	1.728	3936.45	636.570
Minimum	0.034	354.258	118.898
Standard deviation	0.385	785.045	122.440
Skewness	0.686	1.893	-0.499
Kurtosis	3.030	6.329	2.585
	Panel B: Correlation Matrix		
CO_2 Emissions	1.000		
per capita GDP	0.390	1.000	
Energy Use	0.746	0.540	1.000

Source: Authors' Computations

The correlation analysis is performed to appraise the associations among the variables. Specifically, it is used to evaluate the strength of the linear relationship between the variables. From the lower panel, the correlation matrix shows that both per capita income and energy use have positive associations with the dependent variable, CO_2 emissions per capita. Similarly, a positive association exists between the two regressors, and there is no evidence of collinearity that may lead to biased outcomes.

3.2 Model Specification

The present study investigates whether per capita income and energy use contribute or impede environmental degradation measured by the amount of carbon emissions in five selected South Asian countries from 1990 to 2018. The empirical model is implicitly specified as:

$$CO_{2_{it}} = f(PC_{it}, ENU_{it}) \quad [1]$$

Where, $CO_{2_{it}}$ is carbon emissions per capita; PC_{it} is GDP per capita; and ENU_{it} is non-renewable energy consumption per capita. Equation [1] is expressed in its explicit form, and the variables converted to their natural logarithms not only to control for outliers by removing large values that may create bias but primarily to establish elasticity relationships. The trivariate log-linear model is expressed as:

$$\ln CO_{2_{it}} = \beta_0 + \beta_1 \ln PC_{it} + \beta_2 \ln ENU_{it} + \varepsilon_{it} \quad [2]$$

Where, ln denotes the natural logarithm, i represents the number of countries, $1, 2, \ldots, N$, t captures the time dimension $1, 2, \ldots, T$, β_j are the parameters interpreted as elasticities and ε is the stochastic error term. From expectations, increase in per capita GDP should exacerbate carbon emissions and therefore deteriorate the environment. A rising income may lead to ostentatious living necessitating the consumption and production of goods, which may warrant the use of technologies that will provoke more carbon emissions. Similarly, an increase in non-renewable energy use which is the practice of adopting non-replaceable energy sources such as coal, petroleum, natural gas, and fossil fuel contributes to rising carbon emissions and environmental degradation. Hence, positive coefficients are expected for both variables.

4 Analytical Procedure and Results

To address the study objectives, Equation [2] is analysed with a blend of analytical techniques which are deployed to investigate various aspects of the relation and to observe the consistency of the study outcomes. These techniques some of which have been used by similar studies (Ali, Anwar, & Nasreen, 2017; Rahman *et al.*, 2020; Yazdi & Dariani, 2019) are discussed alongside their results in sequential order.

4.1 Cross-Sectional Dependence (CSD) Test

The empirical analysis starts with the application of the cross-sectional dependence test among the countries to determine the suitable methods to apply. The advantage of panel data analysis ranges from better degrees of freedom, greater efficiency of the estimates, and reduced occurrence of multicollinearity among the variables (Ditzen, 2016). However, the risk of cross-sectionally dependent panels is very high due to the close proximities of the units and given the possibility of sharing common features. In the event of cross-sectional dependence (CSD) in the data, biased estimates and inferences will occur (Pesaran, 2004). To forestall such, the

study engages the Pesaran (2004, 2007)[4] test for cross-sectional dependency (CD) which can be applied to small and large panels. The null hypothesis of no CSD which can be rejected at the 1%, 5% and 10% significance levels is expressed as:

$$CD = \sqrt{2T/N(N-1)}\left(\sum_{i=1}^{N-1}\sum_{k=i+1}^{N}\hat{\rho}_{i,k}\right) \quad [3]$$

The results of the CD test which is presented in Table 3 reject the null hypothesis of no cross-sectional dependence at the 1% significance level suggesting that any shocks in one country may be transmitted to other countries among the South Asian countries.

Table 3 Cross-sectional Dependence Test

Variable	CD-test	*p*-value
CO_2 per capita, log	13.968[a]	0.000
per capita GDP, log	16.822[a]	0.000
Energy per capita, log	13.665[a]	0.000

Note: [a] indicates the statistical significance at 1% level.
Source: Authors' Computations

4.2 Slope Homogeneity Test

On the other hand, the validity of the non-constancy of slope homogeneity in the coefficients among cross-sections instigates the importance of slope heterogeneity (Eberhardt & Teal, 2012; Gunduz, 2017). For this reason, we employ the slope homogeneity test by Pesaran and Yamagata (2008). This test extends the Swamy (1970) test called the $\tilde{\Delta}$ test. While the former is applied to panels with relatively large/small cross-section (*N*) to the time dimension (*T*), the latter is applied to a cross-section that is relatively small to the time dimension. The modified version of Swamy's statistics is extended to both balanced and unbalanced data. The standardised statistics for unbalanced data is given by

$$\tilde{\Delta} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\hat{d}_i - K}{\sqrt{2k}}\right) \quad [4]$$

The test is asymptotically $\Delta \sim N(0,1)$ with a null hypothesis of slope homogeneity, and where d_i in weighted form represents the difference between *N* estimator and the pooled estimator $\left(\left(\hat{\beta}_I - \hat{\beta}_{WFE}\right)' \frac{X_i' M_{ti} X_i}{\hat{\sigma}^2}\left(\hat{\beta}_I - \hat{\beta}_{WFE}\right)\right)$. The test can be expressed in terms of normally

[4]Pesaran (2015) extends the analysis of the Pesaran (2004) CSD test and shows that the implicit null of the test is weak cross-sectional dependence. Interested reader is referred to Section 29.7 "Testing for error cross-sectional dependence" in Pesaran, HM (2015) Time Series and Panel Data Econometrics, 1Ed., Oxford Press

distributed errors using mean-variance bias-adjusted $\hat{\Delta}$ (Bersvendsen and Ditzen (2020)) and it is expressed as:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\sum_{i=1}^{N}\hat{d}_i - K}{\sqrt{Var(\hat{z}_i T)}}\right) \quad [5]$$

Where $Var(\hat{z}_i T)$ equals 2k (T-K-1)/(T-K+1) . The result of the slope homogeneity test, which rejects the null hypothesis of a homogeneous slope at the 1% level is presented in Table 4. The outcome of the slope homogeneity test supports the engagement of the DCCE-MG technique for the individual countries.

Table 4 Slope Homogeneity Test

Delta	Model 1
$\tilde{\Delta}$	6.931[a]
$\tilde{\Delta}_{adj}$	7.562[a]

Null hypothesis (H_0): slope coefficients are homogenous.
Note: [a] indicates the statistical significance at 1% level.
Source: Authors' Computations

4.3 Panel Unit Root Tests

Given the presence of cross-sectional dependence, the data is subjected to second-generation unit root tests to avoid spurious results. The cross-sectional augmented Im, Pesaran, and Shin (CIPS) and cross-sectional augmented Dickey-Fuller (CADF) tests developed by Pesaran (2007) are engaged. These techniques account for cross-sectional dependence among the constituent units. The equation for the CADF is stated as:

$$\Delta y_{it} = a_i + d_i y_{i,t-1} + c_i \bar{y}_{t-1} + b_i \Delta \bar{y}_t + u_{i,t} \quad [6]$$

Where z_{it} represents the variable being tested. The CIPS test, which is the augmented variant of Im, Pesaran, and Shin (2003) unit root test, is expressed as:

$$CIPS(N,T) = \bar{T} = N^{-1}\sum_{i=1}^{N} t_i(N,T) \quad [7]$$

Where N and T are the numbers of cross-sections and years, respectively. The left-hand side of Equation [7] is the unit root test for heterogeneous panels while on the right-hand side the term t_i is the ordinary least squares (OLS) *t*-ratios employed in cross-sectional averaged

augmented Dickey-Fuller (ADF) regression. The results of both the CADF and CIPS unit root tests are presented in Table 5 and indicate that all the variables are stationary at first difference.

Table 5 Panel Unit Root Tests

Variable	CADF	CIPS
Level		
CO_2 per capita, log	-0.913	-1.489
per capita GDP, log	-1.382	-1.684
Energy per capita, log	-1.250	-1.250
First differences		
Δ CO_2 per capita, log	-2.480[b]	-5.058[a]
Δ per capita GDP, log	-3.270[a]	-4.423[a]
Δ Energy per capita, log	-4.309[a]	-4.309[a]

Note: [a] and [b] indicate statistical significance at 1% and 5% levels, respectively.
Source: Authors' Computations

4.4 Panel Cointegration Tests

To assess whether a long-run relationship exists among the variables, the second generation panel cointegration tests proposed by Westerlund (2007) is deployed. This technique is suitable in the presence of CSD in the data. The null hypothesis of no cointegration, which is rejected at the 1% and 5% significance levels are shown in Table 6. These outcomes further assert the presence of long-run cointegrating relationship among the variables. Hence, there exists a long-run relationship between energy consumption, economic growth (income), and environmental degradation (CO_2 emissions) in the South Asian region.

Table 6 Westerlund Panel Cointegration Test

Panel Westerlund Cointegration	Test Statistic	Robust *p*-value
Gt	-3.148[a]	0.000
Ga	-9.645[b]	0.020
Pt	-6.747[b]	0.040
Pa	-6.090	0.300

Note: [a, b,] and [c] indicate statistical significance at 1%, 5%, and 10% levels, respectively.
Source: Authors' Computations

4.5 Dynamic Common Correlated Effects-Mean Group

To address the first study objective of testing for long-run relationship among the variables for the full sample, the DCCE-MG technique proposed by Ditzen (2016, 2018) is adopted for several reasons: (1) it accounts for both heterogeneous and homogeneous coefficients, (2) controls for cross-sectional dependence; (3) supports instrumental variable regressions; (4) suitable for unbalanced panels; (5) corrects for small sample bias (6) uses the jack-knife correction method and the recursive mean adjustment (Chudik & Pesaran, 2015; Pesaran,

2006). This technique is important because it helps in identifying effects for each cross-section separately and account for unobserved dependencies between the units. The DCCE-MG equation is specified as:

$$y_{i,t} = \lambda_i y_{i,t-1} + \beta_i x_{i,t} + \sum_{I=0}^{PT} \delta_{i,I}^{'} \bar{Z}_{t-I} + \epsilon_{i,t} \quad [9]$$

Where, $\bar{Z}_t = (\bar{y}_t \bar{y}_{t-1,} \bar{x}_t)$. Thus, the Mean Group estimates are: $\hat{\pi}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\pi}_i = (\hat{\lambda}_i, \hat{\beta}_i)$. The assumption of a long-run homogeneous slope is conditioned for the full sample while that of long-run slope heterogeneity is assumed for the individual country analysis based on the outcome of the Pesaran and Yamagata (2008) slope homogeneity test in Table 4. The results of the DCCE-MG analysis shown in Table 7 reveal a statistically significant positive elasticity effect of the past level of CO_2 emissions and contemporaneous energy consumption on CO_2 emissions at the 5% and 1% levels, respectively. It implies that a percentage change in the previous year's emissions level is associated with an increase in CO_2 emissions by 0.175 per cent, on average, *ceteris paribus*. This also indicates that carbon emissions is rising in the selected countries, which by extension implies the persistency of environmental degradation. This outcome contradicts Aye, Edoja, and Charfeddine (2017) who found a positive but insignificant relation and Ghazali and Ali (2019) that indicate negative and significant previous year's emissions on the current CO_2 emissions, respectively.

Table 7 DCCE-MG Results

Variables	CO_2
CO_2 per capita_1, log	0.175[b] (2.47)
Energy per capita, log	1.009[a] '(4.99)
per capita GDP, log	0.16 (0.22)

Note: [a, b,] and [c] indicate statistical significance at 1%, 5%, and 10% levels, respectively; *t*-statistics are in *( )*.
Source: Authors' Computations

The outcomes further suggest that the use of non-renewable energy exacerbates environmental degradation. It shows that the latter exerts a statistically significant positive impact (1.009) on carbon emissions at the 1% level, on average, *ceteris paribus*. The magnitude of impact indicates a one-for-one elasticity relationship such that if the usage of non-renewable energy increases by 100% in South Asian countries, carbon emissions level will rise by 100% which further endangers the environment supporting the energy-led degradation hypothesis. Our findings support related studies (Afridi *et al.*, 2019; Magazzino, 2016b; Nathaniel *et al.*, 2020;

Neagu & Teodoru, 2019). On the other hand, there is no evidence to support the growth-led degradation as economic growth proxied by per capita GDP does not exert any statistically significant effect on CO_2 emissions, though the coefficient is positive. This outcome suggests there is no evidence that economic growth aggravates environmental degradation. In retrospect, the non-significant but positive impact of economic growth on CO_2 emissions may indicate inadequate growth in these selected countries not sufficient to trigger environmental degradation. Similar to other studies (see Ozturk and Acaravci (2013); Salahuddin, Alam, and Ozturk (2016)) with no evidence of growth-led degradation.

4.6 Dynamic OLS and Fully Modified OLS

To test for the robustness of our findings, the FMOLS and DOLS techniques are used. The DOLS is a parametric approach in which lags and leads are introduced to cope with the problem of cross-sectional dependence irrespective of the order of integration and the existence or absence of cointegration. At the same time, the FMOLS is a non-parametric approach used to dealing with serial correlation. Kao and Chiang (2001) extended the DOLS technique to panel data analysis with the following model specification:

$$y_{i,t} = \beta_i^{'} x_{i,t} + \sum_{j=-q}^{q} \delta_{ij} \Delta x_{i,t+j} + \gamma li^{'} Dl_i + \varepsilon_{i,t} \qquad [10]$$

Where, q refers to the number of lags chosen using the appropriate information criteria. The DOLS is suitable for this study because it provides a robust correction of endogeneity in the regressors. Similarly, the use of FMOLS panel data analysis was introduced by Pedroni (1999, 2001). This technique not only gives consistent estimates of the parameters in small sample data but also controls for likely endogeneity of the regressors and serial autocorrelation. Ramirez (2006) simplifies the FMOLS estimator for the *i*-th unit as:

$$\beta_i^* = (X_i{}'X_i)^{-1} (X_i{}'y_i^* - \mathrm{T}\boldsymbol{\delta}) \qquad [11]$$

Where, y^* connotes the transformed endogenous variable, δ is the parameter for autocorrelation adjustment, and T is the number of periods. The results from the FMOLS, and DOLS techniques are presented in Table 8 and indicate that economic growth intensifies CO_2 emissions by 0.61 and 0.29 percent, respectively. Similarly, energy is found to provoke emissions by 0.96 and 1.46 percent, respectively in the long-run and all the relationships are

statistically significant at the 1% level. More so, the evidence is given that both growth-led and energy-led degradation are prevalent in South Asia.

Table 8 FMOLS and DOLS Results

Variables	FMOLS	DOLS
	CO_2	CO_2
Energy per capita, log	0.962[a] (27.486)	1.464[a] (7.431)
per capita GDP, log	0.608[a] (86.857)	0.286[b] (2.252)

Note: [a, b,] and [c] indicate statistical significance at 1%, 5%, and 10% levels, respectively; *t*-statistics are in *( )*.
Source: Authors' Computations

In general, the results from the DOLS and FMOLS analysis are in tandem with those of DCCE-MG, except for per capita GDP that is statistically not significant. This could be because the DCCE-MG technique controls for dependence among these selected South Asian countries. Hence, reliance on the results of the DOLS and FMOLS techniques alone may give flawed and ambiguous outcomes, given the likelihood of common shocks permeating across the countries.

Furthermore, the outcome of the slope homogeneity test supports the use of the DCCE-MG approach for the individual countries. That is, it provides sufficient evidence for heterogeneous slopes for the countries. As a result, Equation [9] is augmented to accommodate country-level analysis, and the results are indicated in Table 9.

Table 9 DCCE-PMG Country-level Results

Variables	Bangladesh	India	Nepal	Pakistan	Sri Lanka
	CO_2	CO_2	CO_2	CO_2	CO_2
CO_2 per capita_1, log	0.173 (1.37)	-0.045[a] (-9.71)	0.108 (0.69)	0.268 (1.15)	0.373 (0.31)
Energy per capita, log	1.452 (0.42)	0.91 (0.71)	0.281[b] (2.11)	1.143 (0.57)	1.262 (0.39)
per capita GDP, log	-1.726 (-1.39)	-0.087[a] (-10.27)	2.832 (0.36)	0.223[a] (3.64)	-1.444 (-0.49)

Note: [a,] and [b] indicate statistical significance at 1%, 5%, and 10% levels, respectively; *t*-statistics in *( )*.
Source: Authors' Computations

Firstly, we find no evidence of continual environmental degradation in Bangladesh, Nepal, Pakistan, and Sri Lanka as the coefficient of the lagged CO_2 emissions is positive but not statistically significant suggesting that past CO_2 emissions is inadequate to deteriorate the environment in these countries. Contrarily, India shows a negative and statistically significant impact of its past emissions on contemporaneous level of CO_2 emissions at the 1% level (see also Ghazali and Ali (2019); Shaari, Karim, and Abidin (2020)). It implies that the past

emissions level do not adversely contribute to environmental degradation. The most plausible reasoning could be the gradual departure from using non-renewable energy sources to environmentally friendly energy sources. In a different sublet, per capita GDP shows a statistically significant negative (-0.087) impact on CO_2 emissions at the 1% level in India but a statistically significant positive (0.223) impact in Pakistan, also at the 1% level. These outcomes suggest that a percentage change in per capita GDP reduces the emissions level in India by 0.08 percent. In comparison, it increases that of Pakistan by 0.223 percent, on average, *ceteris paribus*. Hence, the growth-led sustainability holds for India while growth-led degradation holds for Pakistan. Further points reveal that non-renewable energy tends to exert harmful effects on the environment in South Asia, though the impact is statistically not significant, except in Nepal. This indicates that energy consumption contributes significantly to environmental degradation in Nepal, implying a more severe and harmful environment emanating from the energy source in the country instituting the energy-led degradation stance.

4.7 Dumitrescu-Hurlin non-Causality Test

Finally, this study addresses the fourth objective which is to establish the direction of causality between the variables by deploying Dumitrescu and Hurlin (2012) causality tests (hereafter, referred to as D-H) which are shown in Table 10. The D-H technique is adopted because it accommodates heterogeneity and cross-sectional dependence among the constituent units that make up the panel which other Granger causality test do not have. Similarly, the technique is capable of providing reliable estimates for small sample data. Danish, Ulucak, and Khan (2019) constructs the D-H model as:

$$Y_{i,t} = \delta_i + \sum_{i=1}^{P} \gamma_i^{(\rho)} X_{i,t-n} + \sum_{i=1}^{P} \varphi_i^{(\rho)} Y_{i,t-n} + \varepsilon_{i,t} \qquad [12]$$

Where, n implies the lag length, X and Y are the variables in the panel for n cross-sections in time t, $\gamma_i^{(\rho)}$ and $\varphi_i^{(\rho)}$connote the autoregressive parameters and regression coefficient across the constituent units. The hypotheses that guide the DH model are given as:

$H_0 : \gamma_i = \cdots \gamma_p = 0 \qquad \forall_i = 1, 2, \ldots, N$

Against the alternative:

$H_i : \gamma_i \neq \cdots \gamma_p \neq 0 \qquad \forall_i \neq 1, 2, \ldots, N$

Table 10 Causality Results

Equation Variables	Excluded Variables	W-stat
CO_2 per capita		
	per capita GDP	3.628[a]
	Energy per capita	2.456[c]
per capita GDP		
	CO_2 per capita	0.179
	Energy per capita	0.766
Energy per capita		
	CO_2 per capita	3.11[a]
	per capita GDP	6.287[a]

Note: Ho: Excluded variable does not Granger-cause Equation variable; Ha: Excluded variable Granger-causes Equation variable; [a] ($p<0.01$), [b] ($p<0.05$), and [c] ($p<0.1$) indicate statistical significance at the 1%, 5%, and 10% levels respectively.
Source: Authors' Computations

Table 10 details the result from the Dumitrescu–Hurlin test, which reveals a one-way causal relation from economic growth to environmental degradation ("growth-led degradation"). Hence, it is inferred that economic growth promotes environmental deterioration. Also, the results reveal a bi-directional relationship between non-renewable energy and environmental degradation ("feedback hypothesis" and "energy-led degradation"). This outcome implies that the previous value of energy consumption is significant enough to explain the future dynamics of environmental degradation with feedback effects. Further, the results exhibit a one-way causality from economic growth to non-renewable energy ("conservation hypothesis"), indicating that as economies grow energy consumption increases.

5 Conclusion and Policy Implications

The relationship among environmental degradation proxied by carbon dioxide emissions, non-renewable energy, and per capita GDP for the past few decades has fuelled a series of debates with attracted attention across the globe. As such, this study contributes to the debate by engaging an unbalanced panel data of five selected South Asian countries (Bangladesh, India, Nepal, Pakistan, and Sri Lanka) covering 1990 to 2018. Our results provide sufficient evidence to address the study objectives. That is: (1) energy-led and growth-led degradation exist in the data; (2) the results from the individual countries are significantly different with Nepal indicating energy-led degradation, Pakistan with growth-led degradation and India with growth-led sustainability; and (3) economic growth Granger-causes energy use and environmental degradation (unidirectional causality) while a bi-directional causal relation obtains between degradation and non-renewable energy.

Policy implications derived are not far-fetched. The finding above does not provide only concerted information for policymakers in these countries, but individual details for each country's stakeholders since the evidence of heterogeneity implies that each nation in the panel of the selected region (South Asia) may develop its environmental easing policies. Also, the stakeholders should collectively put in place effective energy management in charge of reducing the negative effect of energy-consuming industries and energy-consuming technologies to ensure pollution easing in these countries. Further, the rising income from economic growth by these countries should be devoted to acquiring resources that will minimise environmental damage and, in turn, boost output.

Lastly, tackling climate change and ensuring a sustainable environment (SDG13) requires that de-carbonisation measures be pursued to enable a healthy environment that will reduce health impacts due to energy-related air pollution (SDG3) by 2030. However, there exists a dilemma for developing economies like those of South Asia who may require a trade-off. This is because the drive to pursue economic growth agendas will elicit more carbon emissions which will further degrade the environment. We leave this open for more constructive policy discourse on the quagmire of growth-led degradation.

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