Contents lists available at

Economic Dialogue: International Journal of Policy & Practice

Journal Homepage: https://journal.vu.edu.pk/EDJ

ISSN No. (Online): 3106-6593

ISSN No. (Print): 3106-6607

Impact of Energy Consumption on Environment: A CS-ARDL Approach for BRICS Countries

Muhammad Muddassir *

Independent Researcher, Pakistan

ARTICLE INFORMATION

Keywords:
Energy Intensity, BRICS, Urbanization, CS-ARDL, CO2 Emissions

ABSTRACT

The urbanization in BRICS is expanding rapidly and to meet the requirements of that increased population. To meet the energy requirements of that increasing population heavy industries and fossil fuels are being used. This study examines the effects of energy use, gross domestic product, renewable energy and urbanization on carbon emissions. To account for the heterogeneity and strong cross-sectional dependence in BRICS nations i.e. Brazil, Russia, India, China, South Africa and mixed order of variables, the most favorable technique known as cross-sectionally augmented autoregressive distributive lag (CS-ARDL) has been used for estimation. The results show that energy use, GDP and urbanization are positively related to carbon emissions, and renewable energy is negatively related. As the panel heterogeneity is concerned, long run relationship of variables across the panels is captured by cross-sectional autoregressive distributed lag (CS-ARDL) and for robustness Augmented Mean Group Estimations (AMG) and pooled mean autoregressive distributed lag (PMG-ARDL) are estimated. As the BRICS countries have extreme heterogeneity which leads to mixed magnitude of coefficients of variables across each country, so AMG estimates this heterogeneity effectively overall. This study relates the magnitude of use of energy intensity to the use of renewable energy for policy formulation on the degradation of environment.

1. Introduction

Industrialization is a significant indicator of the economic growth and technological advancement as well social welfare globally. It changes agricultural economies into industrial countries. The industrial development also brings about huge adverse effects on the environment through the release of CO_2 in atmosphere. This is a major contradiction of industrialization process where on one side there is an improvement in production and on the other side there is degradation of the environment. This situation is more of a concern for developing nations since they depend on industrial development to boost their economic fortunes and they have no proper measures to deal with carbon emissions.

This research will focus environment-energy nexus in BRICS and aims to find out whether energy intensity has a part in the environmental degradation and secondly analyse the effectiveness of renewable energy in minimizing the impact of industrialization on the environment. From mapping these relationships, the project aims at presenting policy briefing factually to policy makers on how industrialization can be boosted without compromising the environmental base.

The rationale for this research comes from the increasing concerns with environment caused by industrialization in developing countries. These states find themselves in an uncanny developmental conundrum. They require industrialization to address poverty, unemployment, and infrastructure deficit. Simultaneously, they are pressured to cut on their emissions and meet international climate change obligations. Literature reveals that industrialization has a direct impact on CO_2 emissions and utilizing renewable energy will diminish undesirable effects. However, little empirical research has addressed these dynamics as part of the broader organising of the economy with a focus on developing economies.

Environmental impacts of industrialization have developed a worrisome aspect in its use, especially in underdeveloped countries where industrial growth rates are high compared to the protection of environmental concerns. Carbon dioxide pollution is caused primarily by industries that is by product of combustion of on fossil fuels. International Energy Agency (2022) estimates that industrial processes and energy consumption generated more than 36.8 billion metric tons of CO_2 in 2022 and developing economy emissions were higher than developed economy emissions because energy intensive industries are heavily used in developing economies and the electricity is generated by using coal. China derives almost 60% of its energy from coal powerplants (Statista 2023) i.e. almost ninety exajoules of energy derived just from coal power plants. Figure 1 describes the CO_2 emissions per capita of the world has an increasing slope. In the beginning the slope rises exponentially but, in the end, it has a variable and a bit reduction in the rate of change of slope i.e. the rate of increasing per capita CO_2 emissions are reducing. In the last year, the slope has become almost constant.

Among the BRICS economies, industrialization policies are usually a central tendency to attain the objective of economic growth alongside the decrements of poverty, and enhanced infrastructure. However, this growth often is not cheap. BRICS emits the total of 47% carbon dioxide per year (2024) which is half the total emission of the world. It is alarming and the policy of BRICS needs to be changed to control this surge of carbon emissions on regular basis. Out of 37.79 billion tones of CO_2 emissions of world 17.67 billion tons are contributed by BRICS. China is leading in emission. China shares 31.5% global share of CO_2 emissions which is 11.9 billion tones. See below Figure 1.

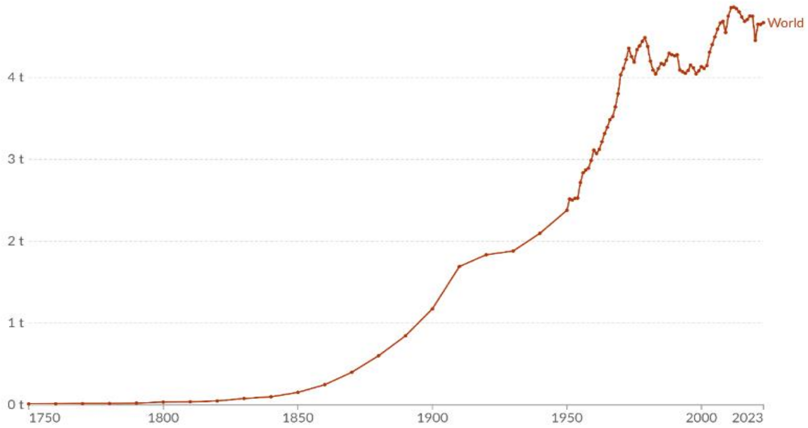

Figure 1. Global per-capita CO_2 emissions have risen sharply since the 19th century
Data source: *OWID , IEA , WDI*

India emits 3.06% of CO_2 which is almost 8.10% of global share. Russia has a global share of 4.81% which becomes 1.82 billion tones. Brazil and South Africa are lying under billion threshold which is 487 million tons and 405 million tons with a global share of 1.29% and 1.065%, respectively. All the emissions are considered at annual basis. In Figure 2 the slope of China and India is increasing at higher rate as compared to others. Embracing industrialization within the circle of the developing economies often leads their economic development, poverty reduction and infrastructure development. Although there are adverse impacts, the process happens most of the time. Acar et al (2018) focused on the SAARC nations and found that, in the initial stages of industrialisation, environmental degradation is caused by industrialisation which is the same is case with BRICS nations. See below figure 2.

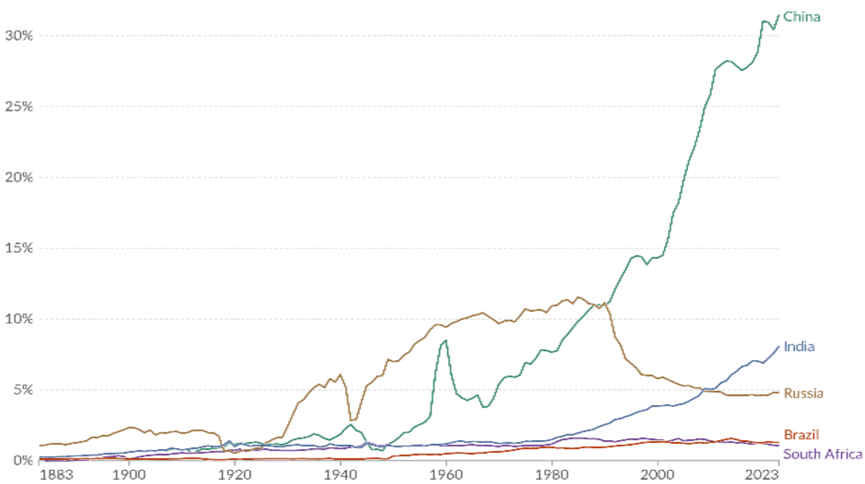

Figure 2. China and India show steep long-term increases in global CO_2 emission shares.
Data source: *OWID , IEA , BP*

With the passage of time all the countries are sharing positive slope of global carbon footprint except for Brazil with a downward trend and a decreasing emission of carbon dioxide. Lowest of all is the South Africa with a straight trend line of carbon emissions. China has an exponential increase of carbon dioxide. India has a moderate increase and a bit of downward trend in some years. The consumption graphs have increasing slope with fossil fuel consumption at a great edge with a 35000 TWH of fossil fuel consumption and 2500TWH of renewable energy consumption in case of China. Other BRICS countries are far behind China in every graph. The use of renewables is considered as a way by which people could to a certain level reduce the negative contribution of industrialization to the environment. Renewable power generation is found to support declining CO_2 emissions. Sachan & Pradhan (2024) showing governance indicators for BRICS countries have also proved that for a nation to Industrialise and build industrial structures without detriment to the environment is possible. These findings suggest that governance reforms and renewable energy can also explain the environmental consequences of industrialisation. See below Figure 3.

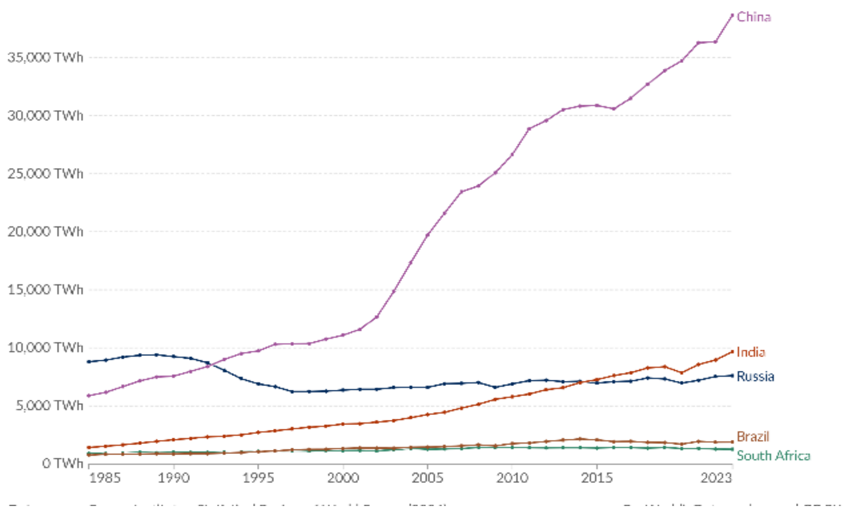

Figure 3. China's fossil-fuel energy consumption far exceeds that of other BRICS nations.
Data source: *OWID* , *IEA* , *EIA*

The fuel type usage of China and the CO_2 emissions are compared in Figure 5. More CO_2 is given off by coal combustion than by other types and China gets 54% of its energy from coal in 2024. The large variation in fuel use makes China emit lots of CO_2 as coal contains higher carbon chain which gives off much CO_2. Coal consumption should be reduced in China which holds 31.5% of global CO_2 shares. See below Figure 4.

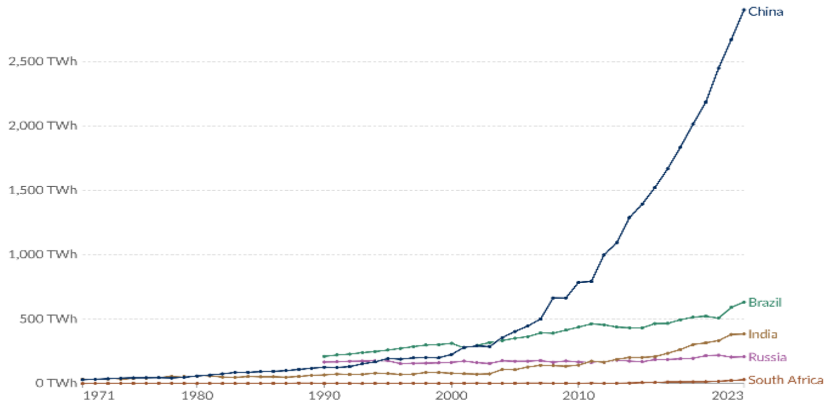

Figure 4. China’s renewable-energy generation has expanded rapidly compared with other BRICS countries.
Data source: *OWID* , *IRENA* , *BP*

Considering the alarming magnitude of degradation of environment globally, this research will seek to contribute knowledge that will help the policymakers to open the economic opportunities without compromising the conservation of the environmental natural resources. To this end, this research aims to contribute to the current literature regarding sustainable industrialization focusing on developing economies and utilizing findings from the current research studies. See below Figure 5.

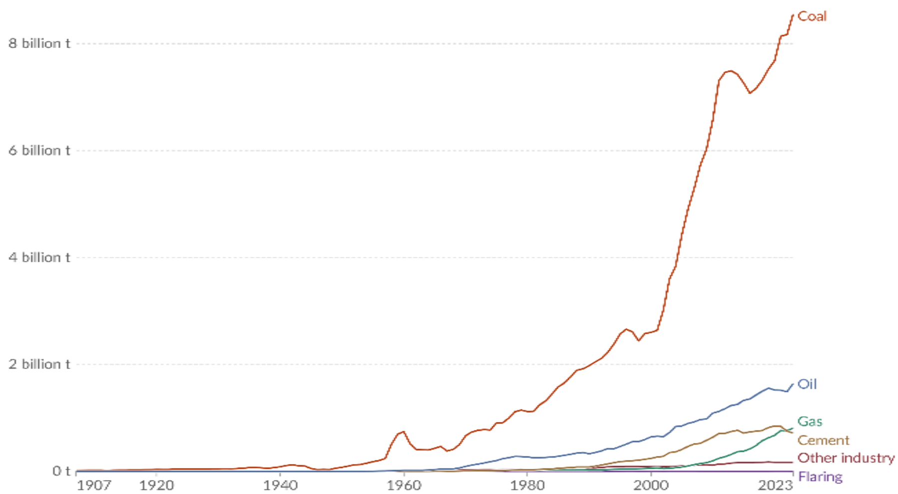

Figure 5. Coal remains the dominant and fastest-growing global CO_2-emitting fuel.
Data source: *IEA* , *BP* , *OWID*

In CO_2 emissions China is leading in BRICS and world since 1980s, and now the graph is increasing at a decreasing rate which means that China is also concerned over this issue and is making some progress by reducing carbon emissions. It is no doubt at the top of the list in the world, but China is also making some progress in controlling the emissions as the renewable energy share of China is increasing following with a decrease in fossil fuel usage and CO_2 emissions. In figure 6, Brazil is leading at almost 50%, on the contrary Brazil is contributing significantly less in CO_2 emission. Other BRICS countries are at the threshold 10% of renewable energy emissions and they need to increase this percentage to control CO_2 emissions. Analysing the connection between industrialization and CO_2 emissions, estimating the contribution of renewable energy, this work offers practical recommendations for national leaders, advocates environmental movement. The outcomes can help inform approaches to attaining sustainable industrial development without negative impacts on environment occasioned by fast economic growth. See below figure 6.

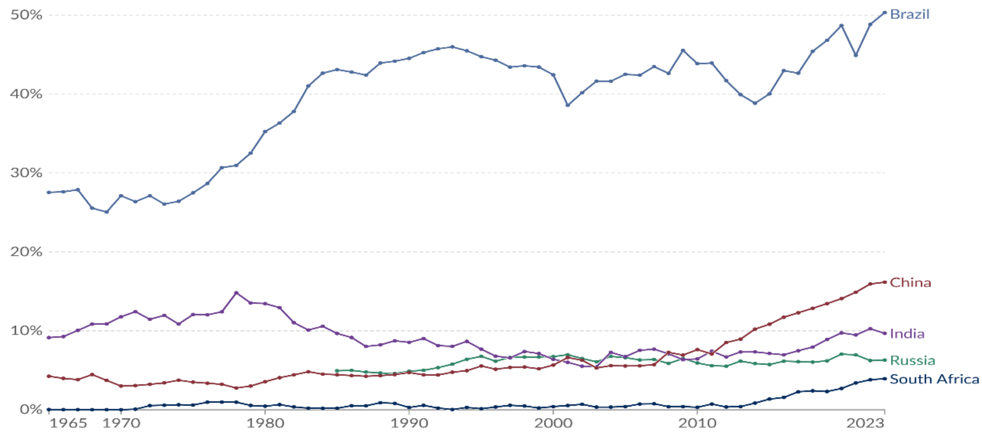

Figure 6. Brazil leads BRICS in renewable-energy share, with others showing lower contributions
Data source: *OWID* , *IEA* , *IRENA*

Table 1: Annual BRICS CO_2 emissions 2023 in billion metric tons

Country	**Annual CO_2 emissions in billion metric tons**	**Percentage share in global CO_2 emission**	**Rank in CO_2 emissions**	**Renewable Energy (TWh)**
World	41.42	100		25064.02
Brazil	1.79	4.32	14	1939.63
Russia	2.22	5.35	4	548.24
India	3.04	7.34	3	1048.72
China	11.61	28.02	1	7666.52
South Africa	0.403	0.97	15	53.09

This work provides significant information for policy makers to formulate policies that would achieve industrialization alongside conservation of environment. The results can help the policymakers in the BRICS economies, in making needed policies to decrease carbon emissions. For instance, Sachan & Pradhan (2024) pointed the role of renewable energy in reducing emissions and the role of governance in moderating emissions also comes out clearly from the study in agreement with the findings of Sachan et al. (2024) examining the case of the BRICS countries. Improving the governance structures and enforcing sound regulations that can support economic development will help policy makers deliver their goals on the economy.

The elevated level of environmental degradation presents in these economies, will provide environmentalists and organizations like the United Nations and the World Bank with leverage when pressing for sustainable development practices in emerging markets. The research points out that renewable energy offers an antidote to the pollution fortunes of industrialization in a way that is consistent with the global climate change initiatives. Wang et al (2024) has indicated how the adoption of green technologies has the possibility of lowering emission, whereby there is a call for intergovernmental collaboration of technology sharing and investment in renewable technology systems. The findings from this research can be enforced at national and regional level that will challenge industries to change to sustainable technologies and practices. Most of the studies associate industrialization as a cause of $\mathrm{CO_2}$ emissions and environmental pollution. Wang et al., (2024) concluded that the industrialization and trade openness policy in South Asia have enhanced the emission of carbon which can be managed by green technology only. Likewise, Acar et al (2018) also pointed out that in SAARC countries, industrial expansion harms environment quality and that later economic development benefit the environment.

Objectives

- To determine that high energy intensity leads to $\mathrm{CO_2}$ emissions in BRICS.
- To evaluate the impact of renewables on mitigating $\mathrm{CO_2}$ emissions in BRICS.

Hypothesis

Null Hypothesis

$\boldsymbol{H_0}$: Industrialization does not increase $\mathrm{CO_2}$ emissions.

Alternative Hypothesis

$\boldsymbol{H_1}$: Industrialization increases $\mathrm{CO_2}$ emissions.

Research Questions

RQ1: To what extent does energy intensity affect $\mathrm{CO_2}$ emissions in BRICS?

RQ2: To what extent renewables mitigate release of $\mathrm{CO_2}$?

2. Literature Review

Industrialization and the condition of the environment is intertwined. The development of economic societies around the world has been dependent on industrialization and during such transformation, a scale of production, technological innovation, and the rate of urban expansion tend to increase. Siddique (2021) has the study on relationship between industrialization and environmental pollution in BRICS. Industrial emissions are related to trade openness and urbanization. Based on energy use and mitigation strategies, Xu, Dong, and Zhang (2022) investigated the effects of industrialization and urbanization on carbon emission intensity in China. Amoah et al. (2024) and Ahmed et al. (2022) investigated the role of industrialization together with trade and FDI in environmental degradation of the Asia Pacific and Sub-Saharan Africa regions, respectively. Voumik et al. (2022) and Akram et al. (2024) examined the impact of industrialization BRICS and SAARC and concluded that indicators of industrialization produce different results according to levels of urbanization and types of energy sources being used. In addition to these economic policies also affect environmental quality. Patnaik (2018) and Wang et al. (2011) examine on sustainable solution by considering clean technology, regulatory framework, and renewable energy adoption.

All the studies conclude that industrialization contributes to the environment at a greater pace than any other indicator. Siddique (2021) and Jadoon et al. (2021) argue that higher carbon dioxide (CO_2) emissions, as well as pollution levels, are observed in South Asia and SAARC countries, equal to higher industrial activities. Industrialization is sometimes coupled with urbanization, by which it is further compounded by this urbanization although such environmental impacts now become regular. Xu et al. (2022) says urban expansion occurs rapidly and puts immeasurable pressure on ecological systems through an increase in urban energy demand and waste generation. Ahmed et al. (2022), Voumik (2023) and Quito et al. (2023), have always had a repeatable outlier accentuating the fact that renewable sources of energy are mitigatory factors against the adverse environmental effects of industrialization. This means that cleaner sources of energy certainly reduce the rate of utilization of fossil fuels and transform the energy sector from fossil fuels to renewable energy. Sachan et al. (2024) and Rehman et al. (2021) say that trade liberalization is a double-edged sword. Its contribution to the economy is matched by an increase in environmentally harmful methods and technologies.

Akram et al. (2024) focused on the harmful role of urbanization in deteriorating environmental in SAARC, while Xu et al. (2022) discussed that some regions in China saw improvements in environmental outcomes when urbanization was combined with policy measures. However, the success of policies was also mixed, with evidence indicating mixed results in the study. Patnaik

(2018) suggested for aggressive policy interventions in South India to reduce industrial emissions, Voumik and Sultana (2022) claim that renewable energy has a significant negative impact on CO_2 emissions. The literature is in favor of the statement that fossil fuel energy consumption contributes to CO_2 and renewable energy reduces those emissions with some exceptions.

This research aims to mitigate the impacts of intensive energy consumption by renewable energy and advancement in technology. Previous study conducted by Voumik et al (2022) focused on the renewables and population and lacked the fossil fuel contribution by a direct indicator. Similarly, Sachan et al (2024) conducted a study on BRICS with some extra indicators like political stability, rule of law etc. but still lacks the contribution of fossil fuels. The research conducted Xu et al (2022) is focused on China. So, the increase of carbon emissions and the simultaneous effects of renewable energy on the emissions have been captured in this model and thus contributes to the gap in literature.

3. Material and Methodology

3.1. Model Specification

Major source of environmental contamination is the emission of CO_2. (Siddique et al 2021) studied the impact of industrialization on environmental pollution. Similarly, (Xu et al 2022) used Extended STIRPAT model to demonstrate environmental pollution with per capita carbon emissions of energy consumption as a dependent variable. Carbon emissions are mostly the byproduct of any type of combustion material. According to IPCC (1996) some of the chemical reactions taking place in chemical industries like cement, lime, dolomite, limestone, soda ash, asphalt, ammonia, and carbide release CO_2 as a byproduct chemical reaction. So, this research will use CO_2 as a dependent variable as used by (Wadanambi et al 2020). Voumik (2022) and Sachan (2024) used CS-ARDL approach with carbon emissions as dependent variable.

The functional form expressed by equation (1) summarizes the variables involved in the research. LCO2 is the function of LEU, LGDP, REN and LURB.

$$LCO2 = f(LEU, LGDP, REN, LURB) \quad (1)$$

The CS-ARDL modelled in equation (2) will be used as a primary method for estimation because BRICS economies are high CD, heterogenous slopes in short as well as long run. It will account for all the heterogeneity which other panel ARDL models like PMG cannot explain. The Φ is error correction term, $\gamma_i \bar{Z}_t$ are cross-ectional averages, β are the long run coefficients and the α are the short run shocks.

$$\Delta LCO2_{it} = \phi_i\left(LCO2_{i,t-1} - \beta_1 LEU_{it} - \beta_2 LGDP_{it} - \beta_3 REN_{it} - \beta_4 LURB_{it}\right) + \quad (2)$$

$$\sum_{J=1}^{2}\alpha_{1j}\Delta LCO2_{i,t-j}+\sum_{k=0}^{1}\alpha_{2k}\Delta LEU_{i,t-k}+\sum_{l=0}^{2}\alpha_{3l}\Delta LGDP_{i,t-l}+$$
$$\sum_{m=0}^{3}\alpha_{4m}\Delta REM_{i,t-m}\sum_{n=0}^{2}\alpha_{5nk}\Delta LURB_{i,t-n}+\gamma_i\bar{Z}_t+\varepsilon_{it}$$

For Robustness checks Augmented Mean Group (AMG) Estimations and PMG-ARDL estimations would be used as expressed in equations (3) and (4) respectively, followed with the required tests. In equations (3) the PMG-ARDL explains the model as β as long run coefficients and α as short run coefficients, λt shows time effects and Φ is the error correction term. The red part in equation (3) is the autoregressive part.

$$LCO2_{it}=\phi\left(LCO2_{i,t-1}-\beta_1 LEU_{it}-\beta_2 LGDP_{it}-\beta_3 REN_{it}-\beta_4 LURB_{it}\right)+$$
$$\sum_{J=1}^{2}\alpha_j\Delta LCO2_{i,t-j}+\sum_{j=0}^{2}\delta_{1j}\Delta LEU_{i,t-j}+\sum_{j=0}^{2}\delta_{2j}\Delta LGDP_{i,t-j}+ \quad (3)$$
$$\sum_{j=0}^{3}\delta_{3j}\Delta REM_{i,t-j}\sum_{j=0}^{2}\delta_{4j}\Delta LURB_{i,t-j}+\mu_i+\lambda t+\varepsilon_{it}$$

The AMG equation (4) is used to estimate long run relationships and it is robust to CD, heterogeneity and non-stationarity. $\delta_i t$ are country-specific trend and α_i country-specific intercept.

$$LCO2_{it}=\alpha_i+\delta_i t+\lambda_t+\beta_1 LEU_{it}+\beta_2 LGDP_{it}+\beta_3 REN_{it}+\beta_4 LURB_{it}+\varepsilon_{it} \quad (4)$$

Panel data from 1990 to 2021 of BRICS countries over the span of 32 years will be used in this research. Data will be obtained from WDI. There are no missing observations in data. Panel Data gives detailed information and is better for econometric estimation as it can minimize estimation bias. Panel data is spread over wide range of variables over time duration which also reduces the chances of heteroskedasticity. It also allows us to control the variables that we cannot observe or measure such as cultural difference in business practice across companies; or variables that change over time but not across factors such as national policies, international agreements etc which means it accounts for individual heterogeneity.

3.2. Dependent Variable

The dependent variable environmental pollution (LCO2) is measured by the natural log of CO_2 emissions (metric tons). This variable reflects the level of carbon pollution caused by human activities, providing a proxy for environmental degradation. It is a critical indicator for assessing the environmental impact of economic growth, energy consumption patterns, and demographic changes. As studied earlier under IPCC every industrial process heavily produces CO_2 as a by product so it will be considered as a main pollution source thus is a dependant variable. Every hydrocarbon combustion varies directly with CO_2 emissions and hence leads to heavy CO_2 emissions.

3.3. Independent Variables

This study uses four independent variables. The first one is the energy usage in kilograms of $1000 GDP. Logged form of this variable is used. This variable will measure the use of fossil fuel energy which has impact on CO_2 emissions. The renewable sources of energy do not release CO_2, so they will not impact on the dependent variable. The second one is GDP. This variable is also used in logged form so it will also be interpreted in terms of elasticity and logged form will scale it down as it includes larger values**.** This variable allows us to see how growth patterns match with the increase in environmental degradation. The third one is renewable energy usage as a percentage of total energy usage. It is already in percentage so logged from will not be used. This is the major variable to control environmental pollution. As per the theory, this indicator has an inverse relation with the dependent variable in BRICS and will be used to control the impact on carbon emissions. The last one is urbanization. It is measured by urban population it will be used in logged form**.** Urban population is meant to increase the amount of carbon emissions.

Table 2: Definition of Variables

Sr.no	Variable Name	Symbol	Unit
i.	Environmental Pollution	LCO2	Natural log of metric tons of CO_2 emissions
ii.	Energy Use	LEU	Natural log of energy use (kg of oil equivalent) per $1,000 GDP (constant 2021)
iii.	Economic Growth	LGDP	Natural log of GDP per capita (constant US$)
iv.	Renewable Energy	REN	Renewable energy consumption (% of total final energy consumption)
v.	Urbanization	LURB	Natural log of urban population

3.4. Methodology

BRICS panel holds cross sectional dependence and heterogeneity so CS-ARDL will be the best model of estimation. Noureen et al. (2024), Voumik et al. (2022) and Sachan et al. (2024) have also conducted research on BRICS with a CS-ARDL approach. For Robustness PMG-ARDL will be used and AMG estimation for long run estimates across the panel.

Table 3: Summary of Methodology

Dependent Variable	Independent Variables	Years	Analysis Technique	Analysis Software	Data Source
Environmental Pollution	Energy Use, Economic Growth, Renewable Energy, Urbanization	1990-2021	PMG-ARDL CS-ARDL AMG	STATA17 EViews13 MS Excel 365	WDI

3.4. Diagnostic Tests

First, correlation matrix and variance inflation factor will be used to check whether the panel suffers from severe multicollinearity. The Pearson Product-Moment Correlation Matrix provides an overview of linear relationships between all variables of the data set and the VIF quantifies how much variance of independent variable is inflated due to linear correlation. Secondly Pesaran, Yamagata (2008) slope homogeneity test will be used to evaluate whether the countries have similar slope or not. The BRICS panel is heterogenous. Then cross-sectional dependence will be evaluated by Pesaran Frees, Friedman, Breusch-Pagan LM tests. Once CD is confirmed we proceed with second generation unit root tests. Here we will use Pesaran CADF Test and Pesaran CIPS test. For robustness and weak CD, the first-generation unit root tests would also be used. Levin, Lin, and Chu (2002), Im, Pesaran, and Shin (2003) and Jörg Breitung (2000) are the first-generation unit root tests that would be used for robustness. Cointegration tests such as Kao Residual Cointegration, Pedroni Residual Cointegration, Westerlund Error-Correction-Based Cointegration would be used for CS-ARDL and for PMG-ARDL the Pesaran-Shin-Smith Bounds Test i.e. ARDL Bounds test would be applied. For the best model selection AIC would be used and the model with lowest AIC value would be preferred. The stars ***, ** and * which denote 1%, 5% and 10% significance levels, respectively.

4. Analysis and Results

MC makes the variance of coefficients large which reduces the significant of coefficients even if they have strong relationship as per the literature.

Table 4: Pearson Product-Moment Correlation Matrix

	LCO2	LEU	LGDP	REN	LURB
LCO2	1.0000				
LEU	0.3599	1.0000			
LGDP	-0.0938	-0.1946	1.0000		
REN	-0.3430	-0.5725	-0.4833	1.0000	
LURB	0.7423	-0.1501	-0.3477	0.3534	1.0000

Author's Computation

To check for the MC problem Pearson product-moment correlation matrix has been used. There are no severe correlations between the regressors. REN is mildly correlated with LEU with negative correlation of -0.5725 which is acceptable and not problematic. Similarly, LURB and LGDP are negatively correlated at -0.3477 and all other regressors have absolute correlation value less than 0.5 so they are at acceptable level of correlation, and some are even less than 0.3 like LGDP−LEU and LURB−LEU which are weak and considered as no concern.

For Multivariate correlation variance inflation factor is used, and the values are under the acceptable range. LURB is under 2 with no concern of multicollinearity. REN, LEU and LGDP are under 5, which is moderate and acceptable range in the context of MC.

Table 5: Variance Inflation Factor and Tolerance

Variable	**VIF**	**Tolerance**
REN	3.30	0.303
LEU	2.64	0.379
LGDP	2.42	0.414
LURB	1.21	0.826
Mean VIF	2.39	

Author's Computation

Tables 4 and 5 conclude that the data does not suffer from severe multicollinearity and hence these variable forms are suitable for estimation.

Table 6: Descriptive Statistics

	LCO2	LEU	LGDP	REN	LURB
Mean	7.058	4.957	8.294	24.931	18.857
Median	7.136	4.975	8.662	18.600	18.853
Maximum	9.443	6.148	9.326	53.000	20.599
Minimum	5.424	4.300	6.276	3.200	16.870
Std. Dev.	1.095	0.427	0.860	17.384	1.029

Author's Computation

From table 6 it is evident that standard deviation of LCO2, LEU, LGDP and URB is low for all variables except REN which shows heterogeneity in BRICS panel in long run and short run which is suitable for CS-ARDL. Mean values of LCO2, LEU, LGDP REN, URB are positive REN has the greatest maximum value in all panels as it is already in percentage and logged form has not been used. All the variables have mean and median values almost equal except for REN and which suggests positive skewness. Others have little to no skewness.

Table 7: Slope Heterogeneity Test

Evaluate	Evaluate Stat	Stat value	p-value	Decision
Pesaran, Yamagata	Δ	15.818***	0.000	Heterogeneous Slopes
	Δ adj	17.549***	0.000	

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

The table 7 shows results of Pesaran, Yamagata (2008) test proves the heterogeneity in slopes thus the coefficients are non-uniform. The null hypothesis says that the coefficients are all uniform, and the test rejects it strongly at 1% level of significance which empirically proves the heterogeneity. The heterogeneity exists because all BRICS countries show high spillovers Ahmed et al. (2022).

Table 8 shows the cross-sectional dependence tests results by Pesaran, Frees, Friedman and Breusch-Pagan LM. The null hypothesis is that there are no cross-sectional dependence and the result of Pesaran, Frees Friedman and Breusch-Pagan LM tests reject the hypothesis at 1% level suggesting evidence of CD.

Table 8: Cross-Sectional Dependence Tests

Evaluate	Stat value	p-value	Decision
Pesaran	-2.726***	0.0064	Cross-sectional dependence Exists
Frees	1.040***	0.0000	Cross-sectional dependence Exists
Friedman	18.241***	0.0011	Cross-sectional dependence Exists
Breusch-Pagan	75.919***	0.0000	Cross-sectional dependence Exists

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 9 shows the results of Pesaran CD test of individual variables for CD and all the variables are rejecting the null hypothesis at 1% level of significance and show convincing evidence of CD.

Table 9: Pesaran CD Test

Variable	CD Stat	p-value	Decision
LCO2	7.73***	0.0000	Cross-sectional dependence Exists
LEU	5.79***	0.0000	Cross-sectional dependence Exists
LGDP	16.14***	0.0000	Cross-sectional dependence Exists
REN	10.52***	0.0000	Cross-sectional dependence Exists
LURB	7.96***	0.0000	Cross-sectional dependence Exists

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 10 summarizes the results of first-generation unit root tests by Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS) and Breitung. It shows the evidence of mixed order in which LEU and REN and LURB are stationary at level I(0). LCO2 and LGDP are stationary at first difference. I(1). There are no I(2) stationary variables which violate the core assumption of ARDL approach. So, we have a mixed order I(0) & I(1).

Table 10: First Generation Unit Root Tests

At Levels I(0)			
Variables	**Levin-Lin-Chu (LLC)**	**Im-Pesaran-Shin (IPS)**	**Breitung**
LCO2	3.3052	0.8704	2.9186
LEU	-3.0721***	-2.5431**	-2.4439***
LGDP	3.7424	0.0796	3.3791
REN	-2.4026 ***	0.3158	-3.2911***
LURB	-15.1062***	23.451***	-1.9928**
At First Difference I(1)			
Variables	**Levin-Lin-Chu (LLC)**	**Im-Pesaran-Shin (IPS)**	**Breitung**

LCO2	-3.8511***	-3.0906***	-3.5997***
LEU	-4.7984***	-4.7866***	-4.4183***
LGDP	-2.4905***	-2.2564***	-4.5221***
REN	-4.9723***	-2.1804***	-6.2520***
LURB	-3.1587***	-0.4167	-3.0419***

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 11 shows the results of Pesaran CIPS test that is second generation unit root test. It also proves that variables are of mixed order. LGDP, REN and LURB are stationary at level at 5%, 1% and 1% level. LCO2 and LEU are stationary at first difference at 1% level. Here again we have a mixed order.

Table 11: Pesaran CIPS Test

	At Level	**First Difference**	
Variable	**CIPS Statistic**		**I(d)**
LCO2	-1.945	-3.263***	I(1)
LEU	-2.288*	-4.799***	I(1)
LGDP	-2.335**	-3.247***	I(0)
REN	-2.611***	-3.869***	I(0)
LURB	-2.585***	-2.823**	I(0)

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 12 shows the results of Pesaran CADF test in also shows the mixed order variables. LCO2, LGDP, REN and LURB are stationary at level at 1%, 1%, 5%, 5%, respectively. The variable LEU is stationary at first difference at 1%.

Table 12: Pesaran CADF Test

	At Level			**First Difference**			
Variable	$\bar{t}$	$Z_{\bar{t}}$	**p-value**	$\bar{t}$	$Z_{\bar{t}}$	**p-value**	**I(d)**
LCO2	-2.813	-2.456	0.007***	-3.263	-3.628	0.000***	I(0)
LEU	-1.869	-0.211	0.416	-3.288	-3.588	0.000***	I(1)
LGDP	-3.499	-4.089	0.000***	-3.247	-3.490	0.000***	I(0)
REN	-2.597	-1.945	0.026**	-2.806	-2.442	0.007***	I(0)
LURB	-2.976	-1.615	0.053**	-4.376	-5.172	0.000***	I(0)

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 13 shows the results of Kao, Pedroni and Westerlund cointegration tests. All tests show evidence of cointegration.

Table 13: Cointegration Tests

Evaluate	Evaluate Stat	Stat Value	p-value	Decision
Kao	Modified D-F	-2.0667***	0.0194	Cointegration
	D-F	-2.1851***	0.0144	Cointegration
	Augmented D-F	-1.7777**	0.0377	Cointegration
Pedroni	Modified Var Ratio	2.0502**	0.0202	Cointegration
	P-P	-3.7033***	0.0001	Cointegration
	Augmented D-F	-3.1674***	0.0008	Cointegration
Westerlund	Group-t statistic	-2.258*	0.0760	Cointegration
	Group-α statistic	-15.062***	0.0000	Cointegration
	Panel-t statistic	-3.312	0.2680	No Cointegration
	Panel-α statistic	-6.198*	0.084	Cointegration

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

In Kao test Modifies Dickey Fuller, Dickey Fuller, and Augmented Dickey Fuller stats are reported in which are significant at 1%, 1% and 5% level of significance. In Pedroni evaluate modified variance ratio, Phillips-Perron and Augmented Dickey Fuller stats are reported in which significant at 5%, 1% and 1% respectively showing convincing evidence of cointegration. Westerlund test shows group-α statistic significant at 1%. Group-t statistic and panel-α statistic are significant at 10%. The panel-t statistics are not significant. For Westerlund cointegration test bootstrapping is used which is effective for small panels. The bootstrapped p values are more robust.

Table 14 shows the results of the Pesaran-Shin-Smith bounds test that is specifically designed for PMG-ARDL but not for CS-ARDL so and for robustness the PMG-ARDL is also included in estimations and shows significant cointegration as described by bounds test. Russia and South Africa show cointegration at 1% level of significance and others are insignificant.

Table 14: Pesaran-Shin-Smith Bounds Test

Country	Stat Value	Critical Value	Decision
BRA	1.847	$F < 3.430$	No Cointegration
RUS	14.215***	$F > 7.578$	Cointegration
IND	2.153	$F < 3.430$	No Cointegration
CHN	0.973	$F < 3.430$	No Cointegration
ZAF	37.097***	$F > 7.578$	Cointegration

Critical Values						
Sample Size	**10%**		**5%**		**1%**	
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
30	3.430	4.624	4.154	5.540	5.856	7.578
Asymptotic	3.030	4.060	3.470	4.570	4.400	5.720

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 15 shows the results of PMG-ARDL estimation. The Automatic Lag selection has been used, and the model selection criteria is Akaike Information Criteria (AIC). The automatic lag selection with unrestricted trend (case 5) has captured the long run relationships with a significant, negative and fast adjustment term. The log likelihood automatic lag selection is high in comparison with other models, and the AIC value is lower. The model used is $ARDL(4{,}4{,}4{,}3{,}4)$. The model includes four lags for dependent variable and three lags for REN and four lags for LEU, LGDP and LURB, respectively. For Annual data with a period of 32 years max 4 lags are sufficient and optimal to avoid overfitting. The major long run variables are significant. The AIC model selection criteria ran through 2500 models to select the best one. The PMG assumes long run estimation to be homogenous and short-run estimation to be heterogenous that's why it cannot be used as the primary estimation measure as BRICS are heterogenous in long as well as short run, rather it can be used as a robustness check for along with the main CS-ARDL estimation.

$$\mathrm{AIC} = 2\mathrm{k} - 2\ln(\hat{\mathrm{L}}) \tag{5}$$

Equation (5) shows that the higher the log likelihood the lower is the AIC value and the lower the AIC value better is the model. Trend specification unrestricted constant and unrestricted trend is appropriate because the variables LCO2, LGDP, LURB show clear upward trend. The variables LEU, REN show clear downward trend.

Table 15: PMG ARDL Estimation Long-run Results

Dependent Variable: ΔLCO2 | Dependent lags: 4(Automatic)

Automatic-lag linear regressors (4 max. lags): LEU LGDP REN LURB

Trend Specification: Unrestricted constant and unrestricted trend (Case 5)

Model selection method: Akaike info criterion (AIC)

Number of models evaluated: 2500 | Selected Model: PMG(4,4,4,3,4)

Variable	Coefficient	Std. Error	t-statistic	p-value
LEU	0.3984***	0.0366	10.899	0.0000
LGDP	0.5381***	0.0343	15.6751	0.0000
REN	–0.0199***	0.0012	–16.4776	0.0000
LURB	0.6141***	0.1758	3.4942	0.0006

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 16 shows the PMG-ARDL short run estimates and the most important term in this estimation is the adjustment term COINTEQ. It is significant at 1% and the speed of adjustment is fast as 89.08% of the deviation from long run is corrected in one year if a short run shock occurs. The system shifts to complete equilibrium in almost $1 / 0.8908 \approx 1.12$ years which is fast equilibrium convergence.

Table 16: PMG ARDL Estimation Short run Results

Variable	Coefficient	Std. Error	t-statistic	p-value
COINTEQ	–0.8908***	0.361	–2.4674	0.015
$\Delta LCO2(-1)$	0.2385	0.210	1.138	0.257
$\Delta LCO2(-2)$	–0.3278	0.241	–1.3581	0.177
$\Delta LCO2(-3)$	–0.0804	0.194	–0.4155	0.679
ΔLEU	0.1621	0.278	0.583	0.561
$\Delta LEU(-1)$	0.0616	0.113	0.543	0.588
$\Delta LEU(-2)$	0.4381**	0.185	2.363	0.020
$\Delta LEU(-3)$	0.198	0.245	0.808	0.421
$\Delta LGDP$	0.2928	0.233	1.259	0.210
$\Delta LGDP(-1)$	0.0315	0.076	0.414	0.680
$\Delta LGDP(-2)$	0.4986***	0.154	3.229	0.002
$\Delta LGDP(-3)$	0.1785	0.196	0.909	0.365

ΔREN	0.0043	0.011	0.385	0.701
ΔREN(−1)	0.0099***	0.004	2.835	0.005
ΔREN(−2)	–0.0019	0.007	–0.256	0.798
ΔLURB	0.3988	3.254	0.123	0.903
ΔLURB(−1)	–2.4655	6.512	–0.378	0.706
ΔLURB(−2)	–0.3646	5.490	–0.0664	0.947
ΔLURB(−3)	–1.6890	1.902	–0.8879	0.376
Constant	–9.5310**	3.994	–2.3864	0.019
Trend	–0.0030	0.004	–0.8017	0.424

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 17 shows the CS-ARDL long run estimates and the lag structure used is CSARDL(2,1,1,1,3). After testing multiple lag structures this lag structure was most stable. The CD statistic is insignificant controlling the CD completely and significant F statistic shows a good model fit.

Table 17: CS-ARDL Estimation Long-run Results

Observations: 145

CS − ARDL(2,1,1,1,3)

F-Statistic: 15.90***

R^2: 0.04

R^2 (Mean Group): 1.00

Root MSE: 0.01

Cross-sectional dependence (CD): -1.52 (p value = 0.1285)

Variable	**Coefficient**	**Std. Error**	**z-statistic**	**p-value**
lr_LEU	0.8835***	0.178	4.97	0.000
lr_LGDP	0.8317***	0.184	4.51	0.000
lr_LURB	0.2125	0.828	0.26	0.797
lr_REN	–0.0303**	0.013	–2.30	0.021

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 18 shows the CS-ARDL short run estimation results. The most important term is the adjustment term (lr_CO2) its negative sign, significance and speed of adjustment. The Adjustment term is significant at 1% level, and it is fast as 1.04% of the shocks are adjusted annually which means that the system will converge towards the equilibrium completely in 1/1.04 ≈ 1 year. To every shock in short run the system will be in complete equilibrium state after one year i.e. a complete adjustment per year which is extremely fast.

Table 18: CS-ARDL Estimation Short-run Results

Variable	Coefficient	Std. Error	z-statistic	p-value
Adjust. Term. (lr_LCO2)	–1.0434 ***	0.090	–11.63	0.000
L. LCO2	–0.0783	0.094	–0.83	0.405
L2. LCO2	0.0349**	0.018	1.980	0.048
LEU	0.8462***	0.135	6.290	0.000
LGDP	0.8409***	0.190	4.430	0.000
REN	–0.0172**	0.008	–2.14	0.032
LURB	0.6268	1.087	0.580	0.564
L. LEU	0.0655	0.206	0.320	0.750
L. LGDP	0.01	0.164	0.060	0.951
L. REN	–0.0145	0.009	–1.56	0.119
L. LURB	–2.1932	2.199	–1.00	0.319
L2. LURB	0.7034	0.569	1.240	0.216
L3. LURB	1.3131	1.006	1.310	0.192

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

Table 19 shows the AMG Estimation results it is used for robustness by Wang et al. (2023) and Gyedu et al. (2024) many other researchers. It controls the unobserved common factors and slope heterogeneity. It is widely supported by literature. It provides long run estimates of all the groups separately accounting for global shocks and CD. Numerous literature studies use AMG to validate the CS-ARDL results.

Table 19: AMG Estimation Results

Country	LEU	LGDP	REN	LURB	Trend	Constant
AMG	0.683***	0.754***	–0.018***	0.498**	1.287***	–12.370***
Avg	(0.1615)	(0.1491)	(0.0056)	(0.2524)	(0.1263)	(4.2394)
BRA	0.992***	0.982***	–0.017***	0.631***	0.152	–18.252***
	(0.1008)	(0.0378)	(0.0009)	(0.0562)	(0.2411)	(0.8309)
RUS	0.961***	0.926***	0.006	0.427	1.347***	–13.532**
	(0.1003)	(0.0517)	(0.0214)	(0.3694)	(0.3831)	(6.3018)

IND	0.442***	0.353***	–0.024***	1.101***	1.320***	–17.926***
	(0.1454)	(0.0792)	(0.0025)	(0.1056)	(0.3394)	(2.6110)
CHN	0.486***	0.837***	–0.017***	–0.112	0.960***	1.901
	(0.0407)	(0.0487)	(0.0009)	(0.1414)	(0.2625)	(2.6489)
ZAF	0.587***	0.578***	–0.026***	0.438***	1.470***	–9.182***
	(0.0776)	(0.1577)	(0.0053)	(0.0807)	(0.5093)	(1.9231)

Author's Computation

***, ** and * denote 1%, 5% and 10% significance levels respectively and SE are in parentheses.

Table 15 and 16 show the PMG-ARDL results of long run and short run, respectively. Energy usage varies directly with LCO2. Every 1% increase in energy usage leads to the 0.398% increase in LCO2 overall. Which is positive in all the BRICS countries, and the coefficient is significant at 1%. Energy utilization also causes short run shocks. For every 1% rise in second lag of energy utilization in short run the LCO2 increase by 0.438% and this short run shock and the coefficient is significant at 5% level. The lagged differenced values of dependent variable in the short run are insignificant which means that the model does not depend upon the previous value of the dependent variable. The LGDP also contributes to the LCO2 significantly in long run. For every 1% rise in the LGDP there is a rise of 0.538% in LCO2 overall and the coefficient is significant at 1% which means that the growth of a country significantly pollutes the environment with LCO2. The LGDP also causes short run shocks i.e. for every 1% rise in the second lag of LGDP there is a short run increase in 0.498% in LCO2 emissions. This short run shock is also significant at 1% level. Renewable energy usage has a significant negative impact on LCO2 in long run. For every 1%-point increase in renewable energy consumption REN there is a 0.019% decrease in the LCO2 overall. The short run shock of renewable energy consumption $\Delta\text{REN}(-1)$ increases LCO2 by 0.0099% and the coefficient is significant at 1% but the next lag $\Delta\text{REN}(-2)$ is decreasing LCO2 by 0.0019% on a 1% increase but this shock is insignificant. Urbanization is related positively to LCO2 and with every 1% increase in LURB there is a 0.614% increase in LCO2 overall. The constant term is significant and negative in our model which clearly shows a decline in the release of LCO2 holding all other variables and adjustment term as constant the average LCO2 decrease each year by 9.53% in the short run across BRICS.

Tables 17 and 18 summarize the results of CS-ARDL long run and short run, respectively. For every 1% rise of energy usage there is 0.883% increase in LCO2. The coefficient is significant at 1% which suggests that LEU has a strong significant and positive relation with LCO2 overall. For every 1% rise in LGDP there is 0.8317% increase in the LCO2 overall and the coefficient is significant at 1% level which suggests that high growth patterns contribute extensively to the LCO2. Renewable energy has a negative impact as it should be. For every 1%-point rise in renewable energy usage there is a decrease in 0.0303% of LCO2 overall. So, renewables serve as a primary source to reduce the LCO2 overall. For every 1%-point rise in urban growth rate there is a 0.2125% increase in the LCO2 overall, but the variable is insignificant. The urban growth rate is contributing insignificantly to LCO2. The adjustment term is amazingly fast which adjusts the 100% disequilibrium in one year. There are also short run shocks. The lagged value of dependent variable is significant. For every 1% rise in the second lag of LCO2 i.e. L2.LCO2 the LCO2 increase by 0.0349% and the coefficient is significant at 5%. For 1% rise in the energy usage in short run the LCO2 increase by 0.846% and the coefficient is significant at 1%. Similarly for a 1% rise in LGDP in short run there is an increase of 0.8409% in LCO2 as a short run shock. For a 1%-point rise in renewable energy usage in short run there is a decrease in 0.0172% in LCO2. The lags of LURB are insignificant in the short run. Voumik et al. (2023) concluded that GDP and urbanization had a positive relationship with LCO2. Noureen et al. (2024) concluded that LCO2 increase drastically with GDP positively. Zardoub (2025) also concluded that GDP is related positively to LCO2, but this study has conflicting results for renewable energy. It says that renewable energy varies negatively with LCO2 in short run, which is consistent with this research, but it varies positively with LCO2 overall which is conflicting. Caglar et al. (2025) also had conflicting results with this research for urbanization which states that urbanization varies negatively with LCO2 overall. Voumik et al. (2023) had consistent with this research for urbanization i.e. LURB varies positively with LCO2. Zhao et al (2025) concludes that GDP varies positively with LCO2 overall which is also consistent with this research.

Table 19 shows the AMG estimation results. The reliability and validity of long run estimates of CS-ARDL model is confirmed by the application of AMG and DCCEMG methods Yousef et al. (2024). With a 1% rise in LEU the LCO2 increase by 0.683% overall and the coefficient is significant at 1%. A 1% rise in LGDP contributes 0.754% positively to the LCO2 in long run and the coefficient is significant at 1%. For 1%-point rise in renewable energy usage there is 0.018% decrease in LCO2, and the coefficient is significant at 1%. If urbanization increases by 1% there is an increase in 0.498% in LCO2 and the coefficient is significant at 5%.

For 1% rise in LEU the LCO2 in BRICS rises by 0.1008%, 0.961%, 0.442%, 0.486%and 0.587% respectively and the coefficients are significant at 1%. As LGDP increases by a 1% in BRICS the LCO2 increases by 0.982%, 0.926%, 0.353%, 0.837% and 0.578% each year, respectively. All the variables of LGDP are significant at 1%. Considering the renewable energy usage, for every 1%

point increase renewable energy consumption in Brazil, China, India and South Africa there is a decrease in 0.017%, 0.017%, 0.024% and 0.026% in LCO2, respectively. The REN coefficient is insignificant and positive for Russia, and the other countries' coefficients are significant at 1%. Urbanization has a positive impact on LCO2 as estimated in PMG-ARDL and CS-ARDL model. For a 1% increase in urbanization in Brazil, India and South Africa there is 0.631%, 1.01% and 0.438%, increase in LCO2 respectively and the coefficients are significant at 1%. Urbanization in China is insignificant and causing 0.112% decrease in LCO2. The Urbanization in Russia is also insignificant but causing 0.427% rise in LCO2. Voumik et al. (2023) in AMG estimations had results consistent with this research for renewable energy in all countries except for the urbanization which had mixed which was negative in Brazil, Russia, India but positively related in China and South Africa.

5. Conclusion

This research has two objectives the first one says high energy intensity contributes to CO2 emissions, and the second one says renewable energy reduces CO2 emissions. To prove the proposed relationship research went through correlation matrix, CD tests, first generation unit root tests (LLC, IPS, Breitung), second generation unit root tests (CIPS, CADF), Cointegration tests (Pesaran Bounds, Westerlund, Pedroni, Kao), PMG-ARDL, CS-ARDL and AMG estimations. This complete econometric procedure led us to the validation of our research questions and objectives i.e. high energy intensity causes CO2 emissions and renewable energy mitigates it. The research concludes that growth that is caused by high energy usage and urbanization have significant contribution to the magnitude of CO2 emissions. While the renewable energy usage has a negative relationship with CO2 emissions. These are the results from CS-ARDL estimations which are validated by AMG estimations and PMG-ARDL estimations. Impact of GDP and energy use is positive overall in BRICS nation.

5.1. Recommendation

In LEU all the BRICS countries are contributing to the CO2 emissions significantly. BRICS reduce only 0.018% of CO2 emissions which is $0.68/0.018 \approx 38$ times less than the release of CO2 by LEU. Firstly, they must control the utilization of coal as a fossil fuel which is the greatest contributor of CO2 emissions. BRICS must reduce this percentage difference of CO2 emissions gradually with a proper policy formation on renewable energy programs. BRICS should make a combined policy at least 1 year as the adjustment of the model is fast enough, and they should set their objective to reduce this percentage difference to a reasonable magnitude each year. Only Russia has positive coefficient of REN which should have separate policy measure as compared to other BRICS countries.

The LGDP in BRICS has positive relation to CO2 emissions as compared to that of LEU variable. On average BRICS contribute 0.754% to release of CO2 which contributing $0.754/0.018 \approx 42$ times more than the reducing impact of CO2 emissions of REN which is four times more massive as compared to LEU. BRICS are heavy industrializing economies, and their economies are mostly dependent upon heavy industry. BRICS should make policies for industries on the release of pollutant as by products because industries operate at large scale and have significant combustion of fossil fuels. Stringent policies should include no direct release of by products in atmosphere the by-products should be refined more till it is left with little or no negative impact on environment. Greater part of GDP should be invested in renewable energy to overcome the emissions.

The LURB in BRICS contribute 0.498% to CO2 emissions which is $0.408/0.018 \approx 27$ times still effectively contributing to CO2 but eleven times less than LEU fifteen times less than LGDP. In urbanization India is with the highest coefficient of 1.10% contribution to CO2 and 0.024% reduction of CO2 which has 46 times more effective in emissions. India should have more strict policies on urbanization with no industrial expansion of already urbanized cities. New cities should be populated instead of expanding the capital cities and other big cities. Only China has negative coefficient for LURB, and all others have positive coefficient.

For LEU and GDP all the countries have positive coefficients so one set of policy for these two variables will be effective. For renewable energy and urbanization there is slight discrepancy in Russia and China, respectively. So, for these two variables two sets of different policies should be designed one for the countries with positive coefficient and other for the countries with negative coefficient.

The government should make energy policy in which there is diverse utilization of renewable energy rather than over dependence on one renewable source. Government should spend in hydro, nuclear, solar, wind, thermal, geothermal, biomass, tidal energy to spread the energy dependence on various sources mentioned in Energy Digital (2024). Public awareness and educations will control vehicle emission and incineration emission (BRICS Summit 2022).

Declarations

All the experiments, estimations, analysis, interpretation and research paper writing were conducted by solely by Muhammad Muddassir. This research did not receive any kind of funding from any private or government sources.

References

Siddique, H. M. A. (2021). Impact of Industrialization and Openness on Environmental Pollution in South Asia.

Xu, L., Dong, T. & Zhang, X. (2022). Research on the Impact of Industrialization and Urbanization on Carbon Emission Intensity of Energy Consumption: Evidence from China. Polish Journal of Environmental Studies, 31(5), 4413–4425.

Wadanambi, R. T., Wandana, L. S., Chathumini, K. K. G. L., Dassanayake, N. P., Preethika, D. D. P., & Arachchige, U. S. (2020). The effects of industrialization on climate change. *J. Res. Technol. Eng*, *1*(4), 86-94.

Ahmed, F., Ali, I., Kousar, S., & Ahmed, S. (2022). The environmental impact of industrialization and foreign direct investment: empirical evidence from Asia-Pacific region. *Environmental Science and Pollution Research*, 1-15.

Jadoon, A. K., Akhtar, S., Sarwar, A., Batool, S. A., Chatrath, S. K., & Liaqat, S. (2021). Is economic growth and industrial growth the reason for environmental degradation in SAARC countries. *International Journal of Energy Economics and Policy*, *11*(6), 418-426.

Akram, H., Li, J., & Watto, W. A. (2024). The impact of urbanization, energy consumption, industrialization on carbon emissions in SAARC countries: a policy recommendation to achieve sustainable development goals. *Environment, Development and Sustainability*, 1-32.

Quito, B., del Río-Rama, M. D. L. C., Álvarez-García, J., & Durán-Sánchez, A. (2023). Impacts of industrialization, renewable energy and urbanization on the global ecological footprint: A quantile regression approach. *Business Strategy and the Environment*, *32*(4), 1529-1541.

Wang, Z., Shi, C., Li, Q., & Wang, G. (2011). Impact of heavy industrialization on the carbon emissions: An empirical study of China. *Energy Procedia*, *5*, 2610-2616.

Sachan, A., Pradhan, A. K., & Mohindra, V. (2024). How do governance indicators, trade openness, industrialization, and population growth affect environmental degradation in BRICS Nations? *Discover Sustainability*, *5*(1), 193.

Patnaik, R. (2018, March). Impact of industrialization on environment and sustainable solutions–reflections from a south Indian region. In *IOP Conference Series: Earth and Environmental Science* (Vol. 120, p. 012016). IOP Publishing.

Voumik, L. C., & Sultana, T. (2022). Impact of urbanization, industrialization, electrification and renewable energy on the environment in BRICS: fresh evidence from novel CS-ARDL model. *Heliyon*, *8*(11).

Amoah, J. O., Alagidede, I. P., & Sare, Y. A. (2024). Industrialization and carbon emission nexus in Sub-Saharan Africa. The moderating role of trade openness. *Cogent Economics & Finance*, *12*(1), 2360803.

Voumik, L. C., & Ridwan, M. (2023). Impact of FDI, industrialization, and education on the environment in Argentina: ARDL approach. *Heliyon*, *9*(1).

Rehman, A., Radulescu, M., Ma, H., Dagar, V., Hussain, I., & Khan, M. K. (2021). The impact of globalization, energy use, and trade on ecological footprint in Pakistan: does environmental sustainability exist? *Energies*, *14*(17), 5234.

Ahmad, W., Mishra, A. V., & Daly, K. (2018). Heterogeneous dependence and dynamic hedging between sectors of BRIC and global markets. *International Review of Financial Analysis*, *59*, 117-133.

Gyedu, S., & Tang, H. (2024). Achieving Carbon Neutrality in the Brics Countries: The Roles of Innovation, Renewable Energy, Economic Growth and Carbon Taxes.

Wang, H., Peng, G., Luo, Y., & Du, H. (2023). Asymmetric influence of renewable energy, ecological governance, and human development on green growth of BRICS countries. *Renewable Energy*, *206*, 1007-1019.

Noureen, T., Malik, M. Z., Khuhro, N. A., & Zafar, M. A. (2024). Exploring the Dynamics of CO2 Emissions, FDI, and Technological Innovation on Economic Growth: Evidence from BRICS Nations by Using CS-ARDL. *Pakistan Journal of Humanities and Social Sciences*, *12*(3), 2456-2469.

Global Carbon Atlas. (2024, June 14). *Global Carbon Atlas*. https://globalcarbonatlas.org/

Seymour, F., & Langer, P. (n.d.). *Consideration of Nature-Based solutions as offsets in corporate climate change mitigation strategies*. World Resources Institute. https://www.wri.org/research/consideration-nature-based-solutions-offsets-corporate-climate-change-mitigation

Environmental Policy in Emerging Economies - *Environmental, Social and Governance (ESG) initiative*. (2023, July 21). Environmental, Social and Governance (ESG) Initiative. https://esg.wharton.upenn.edu/centers-labs/climate-center/environmental-policy-in-emerging-economies/

Acar, Y., Gürdal, T., & Ekeryılmaz, Ş. (2018). Environmental Kuznets Curve for CO emissions: An analysis for developing Middle East, OECD and OPEC countries. *Environmental & Socio-economic Studies*, *6*(4), 48-58.

Wang, Y., Nemitz, E., Tomlinson, S. J., Carnell, E. J., Yao, L., Scheffler, J., ... & Vieno, M. (2024). Response of South Asia PM2. 5 pollutions to ammonia emission changes and associated impacts on human health. *Environment International*, 109207.

Vo, D. H., Ho, C. M., & Vo, A. T. (2024). Do Urbanization and Industrialization Deteriorate Environmental Quality? Empirical Evidence from Vietnam. *SAGE Open*, *14*(2), 21582440241258285.

Ito, T. (n.d.). *Impact of industrialization on environment*. https://www.primescholarslibrary.org/articles/impact-of-industrialization-on-environment-74966.html

Environmental Policy in Emerging Economies - Environmental, Social and Governance (ESG) initiative. (2023, July 21). Environmental, Social and Governance (ESG) Initiative. https://esg.wharton.upenn.edu/centers-labs/climate-center/environmental-policy-in-emerging-economies/

Folk, E. (2024, June 14). The Environmental Impacts of Industrialization | EcoMENA *EcoMENA*.https://www.ecomena.org/environmental-impacts-of-industrialization/

Global Carbon Atlas. (2024, June 14). *Global Carbon Atlas*. https://globalcarbonatlas.org/

Global CO_2 emissions rose less than initially feared in 2022 as clean energy growth offset much of the impact of greater coal and oil use - News - IEA. (2023, March 2). IEA. https://www.iea.org/news/global-CO₂-emissions-rose-less-than-initially-feared-in-2022-as-clean-energy-growth-offset-much-of-the-impact-of-greater-coal-and-oil-use.

Caglar, A. E., Daştan, M., Demirdag, I., & Avci, S. B. (2025). Is low carbon energy consumption sufficient for a sustainable environment in BRICS economies? Evidence from novel Fourier asymmetric CS-ARDL. *Stochastic Environmental Research and Risk Assessment*, 1-16.

Statista. (2024, June 28). *Coal consumption volume in China 1998-2023*. https://www.statista.com/statistics/265491/chinese-coal-consumption-in-oil-equivalent/

Center for Climate and Energy Solutions. (2022, December 1). *Global Emissions - Center for Climate and Energy Solutions*. https://*www*.c2es.org/content/international-emissions/#:~:text=CO2%20accounts%20for%20about%2076,6%20percent%20to%20global%20emissions.

Intergovernmental Panel on Climate Change. (1996). *Revised 1996 IPCC guidelines for national greenhouse gas inventories: Reference manual (Vol. 3, Chapter 2).* Retrieved from https://www.ipcc-nggip.iges.or.jp/public/gl/invs1.html

World Development Indicators | DataBank. (n.d.). https://databank.worldbank.org/FDI-Carbon-emissions/id/9cf0d738

Wooldridge, J. M. (2012). *Introductory econometrics: A modern approach* (5th ed.). Thomson-Southwestern Cengage Learning.

Gujarati, D. N. (2003). *Basic econometrics* (4th ed.). McGraw-Hill Higher Education A Division of The McGraw-Hill Companies.

Greene, W. H. (2018). *Econometric analysis* (8th ed.). New York University the Stern School of Business.

International Energy Agency (2022). CO_2 Emissions in 2022. *Report*, IEA

Our World in Data. (2024b, February 28). *OWID homepage. https://ourworldindata.org/*

Ritchie, H., Rosado, P., & Roser, M. (2023). CO_2 and greenhouse gas emissions. Our World in Data. https://ourworldindata.org/co2-and-greenhouse-gas-emissions

CO2 emissions - Worldometer. (n.d.). https://www.worldometers.info/co2-emissions/

Somoye, O., & Akinwande, T. S. (2023). Can urbanization influence carbon dioxide emissions? evidence from BRICS–T countries. *Journal of Contemporary Urban Affairs*, *7*(1), 164-174.

Zhao, Y., Zhou, H., Jiang, C., Xuan, L., & Chen, L. (2025). Research on the synergizing the reduction of pollution and carbon emissions of new-type urbanization. *Environmental Research Communications*.

Zardoub, A. (2024). Impact of economic growth, renewable energy consumption and energy intensity on CO2 emissions in BRIC countries: An application of CS-ARDL. *Journal of Infrastructure, Policy and Development*, *8*(8), 4312.