Investigating the Role of Human Capital in CO_2 Emissions in Developing Countries

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ABSTRACT

This research aims to explore the role of human capital and other major factors that determine CO_2 emissions over a long period for a world-wide panel of 55 developing countries during 1971-2023. Since first-generation panel estimators have several defects, we use a robust econometric methodology that recognizes and adjusts for cross-sectional dependence (CSD), slope heterogeneity, and non-stationarity. Initial analysis and tests such as Pesaran (2004) and Pesaran (2015) CSD test and Pesaran and Yamagata (2008) Delta test reveal that there are cross sectional dependencies among the sample countries as well as heterogeneity in the slopes. This necessitates the use of Second-generation unit root tests, and relevant panel cointegration tests for heterogeneous slopes to establish the existence of a long-run panel cointegration. The long-run coefficients and elasticities are estimated using Dynamic Common Correlated Effects (DCCE) and Augmented Mean Group (AMG) estimators. Across these specifications, the results indicated that economic growth, fossil fuel based energy consumption and energy use are the primary drivers for environmental degradation with having relatively high degree of responsiveness. Of particular interest is the finding that while human capital (HC) is statistically insignificant in the standard CCE model, but the AMG estimator indicates a significant mitigating effect. This suggests that human capital plays a potential mitigation role. Furthermore, the Juodis, Karavias, and Sarafidis (2021) Granger test indicates the joint causal flow from the selected macroeconomic determinants to CO_2 emissions with profound policy implications.

Keywords: *Human capital, CO_2, developing countries, second-generation unit root test, CSD, AMG, CCEMG*

1. Introduction

The increasing occurrence of extreme weather events and global warming have pushed the reduction of carbon dioxide (CO_2) emissions to the top of international environmental policy agendas. As the main cause of the greenhouse effect, the CO_2 emissions are directly connected with the industrial and economic activities of modern times. While the Sustainable Development Goals (SDGs) and the Paris Agreement call for a quick move towards a low-carbon economy, putting these goals into real practice is still a complicated challenge for both developed and developing economies.

At the heart of this issue is the separation of economic growth from environmental degradation. In the past, industrialization has been driven by a high reliance on fossil energy and intensive energy usage, creating a positive link between increased economic activities and pollution. But as countries develop, the role of "soft" drivers like Human Capital (HC) has started to show up as a possible changing force. Through greater environmental awareness, the development of eco-friendly technologies, and improved management efficiencies, human capital is believed to cancel out the "dirty" effects of traditional industrial growth. Even though there is an enormous body of literature on what causes emissions, there is still no empirical agreement about the mitigation effect of human capital on environmental degradation because several methodological shortcomings are common in earlier research.

Sustainable economic growth is a desired destination for all developing and developed countries in modern times, especially after wide-spread acceptance of SDGs in 2015. In essence, these goals call for achieving economic growth without adversely harming the environment. However, energy production from fossil fuels and then usage of energy for economic growth adversely impacts the

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environmental quality. The pursuit of rapid economic growth and development comes with externalities, which include greenhouse gas emissions, and these are the main contributors to climate change. The effects of environmental change include rising sea levels, the melting of the polar glaciers, depletion of the ozone layer, rise in the temperature of the earth, increased weather uncertainties, decreased crop yields, and decreased labor productivity (Mahmood, Wang, & Hassan, 2019).

The most common greenhouse gas is the carbon dioxide (CO_2) which is extensively used as a proxy of environmental degradation in the environmental-economics literature. Most scholars consider CO_2 as the main marker of the anthropogenic damage to the environment and accordingly use it to monitor the patterns and effects of the policy (Zafar et al., 2019). In recent times, the environmental problems as a primary consequence of economic activity are an acute concern of scholars and policymakers all over the world. The rate of carbon emissions in the world was relatively small until the middle of the 20th century, when it began to increase: approximately 5 billion tons annually in 1950, up to approximately 22 billion tons annually in 1990, and approximately 36 billion tons annually in 2024. Europe and the United States accounted almost 90 percent of such emissions throughout the 20th century. However, over time, the world has evolved, and today, climate changes and their consequences have turned into a significant issue.

Based on recent estimates, the developed countries account for around 29 percent of Greenhouse Gases (GHG) emissions, with Upper Middle-Income Countries (UMICs) accounting for 48 percent, Lower Middle-Income Countries (LMICs) 19 percent and Low-Income Countries (LICs) less than 4 percent (shares of CO_2 emissions are 34%, 47%, 15% and less than 1% respectively)[‡].

Table 1. Share of CO_2 emission in developing countries by regions

Income classification	Share in GHG emissions	Share in CO_2 emissions
Developed countries	29%	34%
UMICs	48%	47%
LMICs	19%	15%
LICs	4%	1%

(Data source: Center for global development, 2026)

It is evident that developing (UMICs, LMICs, and LMICs) countries are now the largest group of carbon and GHG emitters in the world. Therefore, it is pertinent to explore the role of various factors in environmental degradation in this group of countries and identify the relevant mitigating factors as well for policy purposes.

The prime objective of this study is to identify the role of human capital as an important mitigating factor that has the capability to improve environmental quality in developing countries by contributing to reduce carbon emissions. Environmental quality regulation promotes production and consumption activities of various sectors of an economy and, in its pursuit of safe and healthy living conditions for humans and wildlife, generates positive welfare effects (Graff Zivin & Neidell, 2013).

Methodologically, most "first-generation" panel studies use estimators that assume slope homogeneity (treating all countries as identical) and ignore Cross-sectional dependence (CSD). These assumptions seem unrealistic in an era characterized by deep trade integration and global technological spill-overs since such assumptions lead to biased and inconsistent results. In addition, emissions are dynamic processes where current pollution levels are heavily influenced by past behaviors; hence, long-

[‡] https://www.cgdev.org/blog/climate-and-development-three-charts-update, accessed on 20 March 2026

run equilibrium and short-run adjustment speeds should be considered within any estimation framework.

The present study seeks to make three contributions to the literature. First, it uses a balanced panel of 55 developing countries over a period of 53 years (1971–2023) that provides an extensive time series and cross-sectional dimension. Second, the study moves beyond traditional estimators by applying second-generation techniques, namely the Dynamic Common Correlated Effects (DCCE) and the Augmented Mean Group (AMG) estimators that can uniquely deal with all three problems of common shocks, slope heterogeneity, and non-stationarity. Third, it uses the Juodis et al. (2021) Granger non-causality test to go beyond mere correlation and establish a causal flow from macroeconomic drivers to emissions.

The technical arrangement of this paper is as follows; Section 2 presents the literature review highlighting the main trends of research studies and their findings. Methodological framework is provided in section 3; and the econometric methodology is explained in the section 4 along with the diagnostics; and the selected variables, data sources, and summary statistics are given in section 5, and section 6 provides pre-estimation diagnostics, while the results of econometric modelling are given in section 7. Lastly, the conclusions and policy implications for a sustainable global future are given in Section 8.

2. Literature Review

Several studies in relevant empirical literature have focused on the factors that determine carbon dioxide (CO_2) emissions, with special emphasis on human capital, technology, energy, and economic growth. Although many of these works identify similar factors that contribute to environmental degradation, their impacts vary in magnitudes and signs depending on the regions and methods applied. For review purposes, we provide a succinct assessment of such studies and report their key features.

2.1 Panel data studies

One significant area of relevance to this research relates to the role played by human capital in achieving environmental sustainability. From the theoretical perspective, higher educational and skill-building outcomes are likely to contribute to environmental improvement through several avenues, such as higher environmental awareness, more efficient use of resources, and faster adoption of more environmentally friendly technologies. From the empirical perspective, the results support the theoretical position. To illustrate, Hao et al. (2021), through their analysis on the G-7 economies using the Cross-Sectionally Augmented Autoregressive Distributed Lag approach, concluded that human capital, environmental taxation, and the use of renewable energy are significant contributors to better environmental outcomes through the reduction of carbon emissions. Yao et al. (2020) concluded through their analysis on historical data for OECD economies for the period 1870-2014 that higher educational enrollments for higher educational qualifications are likely to contribute to significant reductions in carbon emissions.

Some studies have found the moderating role of education in the relationship between economic growth and environmental performance. Khan (2020) employed panel data from 122 countries over the period 1980-2014 and employs the Hansen threshold model to examine the impact of human capital formation on environmental performance. The results of this study suggest that with an increase in educational attainment, it is possible to reduce negative environmental impacts and pollution. In other words, with an increase in human capital formation, it is possible to move to a higher level of environmentally friendly technologies. In this context, education is considered a mitigator that reduces the positive relationship between growth and pollution.

Aside from human capital, there is emphasis on technological innovation and green technologies in the relevant literature. Technological innovation is often considered as the major channel through which it is possible to decrease carbon intensity while maintaining high economic growth. However, there is limited and mixed evidence from the empirical literature. In this context, Dauda et al. (2019) explore the interrelation between innovation, economic growth, and carbon emissions on the basis of data from developed and developing economies. The authors' findings suggest that innovation has a negative effect on carbon emissions in developed countries; however, innovation is associated with increased carbon emissions in the context of Middle East and North African region and BRICS countries. This implies the possibility of differentiated impact of innovation on environmental sustainability across the level of development achieved.

The energy-environment link is another well-established relationship in the literature. Energy consumption is widely acknowledged as one of the key drivers of carbon emissions, particularly in countries with high dependence on fossil fuels. For instance, Chontanawat (2019) finds robust causality between energy consumption and carbon emissions in ASEAN countries. This implies that countries in ASEAN may focus on improving energy efficiency in order to reduce environmental degradation in the region. Furthermore, structural factors such as globalization, urbanization, and resource dependence have been explored as potential determinants of environmental degradation. Nathaniel et al. (2021), in their analysis of Latin American and Caribbean economies using AMG and CCEMG methods, highlight the intricate relationship between these structural factors and carbon emissions.

Some recent studies such as Rock Voda et al. (2026), Sahu et al. (2024) and Özbay and Duyar (2022) also find favorable role of education and human capital in sustainable development and reducing carbon emissions in case of developed countries especially. However, more research is required in case of developing countries that this study intends to contribute to the relevant literature.

2.2 Time-series studies

In terms of the time-series analysis, some studies indicate that human capital can help mitigate environmental degradation through cleaner production methods and increased usage of renewable sources of energy. For instance, Mahmood et al. (2019) in their 3SLS and ridge regression model of Pakistan indicate that human capital and renewable sources of energy help reduce CO_2 emissions in the country. Similar results are also observed in a study conducted in case of the United States of America by Zafar et al. (2019), where human capital is indicated to reduce ecological footprints in the country. Moreover, human capital is also indicated to reduce deterioration of environment in a study conducted in Pakistan by Bano et al. (2018), where it is indicated that human capital leads to a reduction in the carbon emissions both in the short and long run in the country.

However, there are also studies that indicate that human capital does not significantly reduce environmental deterioration. For instance, in a study conducted in China and using a long-run dataset, Sarkodie, Adams et al. (2020) indicate that human capital increases environmental pressure in China. Similarly, in a study conducted in case of Pakistan and using a ARDL model with structural break, Danish et al. (2019) indicate that human capital and ecological footprints are not significant in the country. Moreover, in a study conducted in case of Indonesia and using a VEC-based Granger causality model, Bashir et al. (2019) indicate that CO_2 emissions and human capital are not significant in the long run in the country.

Yet some other studies focus on other aspects of macroeconomic factors that affect carbon emissions. For instance, Ohlan (2015) examined the Indian case with an ARDL model and found that economic growth, population density, and energy consumption increase carbon emissions significantly.

It also found that trade openness has no impact on carbon emissions. Acharyya (2009) found that there is a positive relationship between economic growth, foreign direct investment, and CO_2 emissions in India. It supports the 'Pollution Haven Hypothesis'.

Overall, it appears that the existing literature presents mixed findings in terms of the interrelationship between environmental sustainability and human capital. Although there is evidence of human capital contributing to mitigating greenhouse gas emissions through improved levels of education and skills, there is also evidence of its insignificance and even negative impact depending on the structure of the country's economy, its energy dependence, and its level of development.

Therefore, in order to address such limitations of first-generation panel data methods, this research uses the panel data techniques from the second-generation such as DCCE and AMG to find out the determinants of CO_2 emissions for developing countries over the period 1971-2023. In addition to this, we also examine the direction of causality between macroeconomic variables and CO_2 emissions by using a recent panel Granger non-causality test that has been proposed by Juodis et al. (2021). These techniques are used for developing a better understand the dynamics of environmental degradation over the long run time horizon and contribute to relevant literature.

3. Methodological framework

The effects of different economic factors especially economic growth on the environment can be measured and analyzed with the help of two different frameworks. The former is the Environmental Kuznets Curve (EKC) suggested by Grossman and Krueger (1995). It is more suitable to use EKC to determine the transformation of the environment and expound relationship between climate changes as outcome of economic growth. In such a manner, EKC is an inverted U-shaped quadratic relationship between economic growth and the carbon dioxide emission (Khan et al., 2018).

The second method used in relevant literature is the Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) that is an econometric and stochastic approximation of an earlier mathematical identity called Impact of Population, Affluence, and Technology (IPAT). As York et al. (2003) present, the IPAT is commonly expressed as a mathematical identity created by Ehrlich and Holdren (1971). Later on, Dietz and Rosa (1994); Dietz and Rosa (1997) reformulated the IPAT identity and developed it into the STIRPAT as a stochastic model for empirical estimations. The standard IPAT is usually written as an identity (equation 1):

$$I=\alpha P^{\beta} A^{\gamma} T^{\delta} \varepsilon \qquad (1)$$

Where 'I' represents environmental impact, P is population, A is affluence, and T is technology. The empirical researchers use the variables in additive logarithmic form in the afore-mentioned equation for estimations and hypothesis testing. In this way, the STIRPAT is expressed in equation 2 as:

$$ln\,(I) = \alpha + \beta lnP + \gamma\, lnA + \delta lnT + \varepsilon \qquad (2)$$

As Wei (2011) noted, the stochastic model STIRPAT may be applied for assessing the causal effects of relevant factors on environment. In the existing literature reviewed for this study, it is found that different extensions have been made in basic Eq. 2 to include other determinants and drivers of environmental impacts, and different proxies have been used for the above-mentioned variables as well. For example, the population (P) growth rate, population, and population density have been used as proxies for population (P); technology (T) is proxied either by industrialization, or energy composition, or energy composition; and affluence (A) is proxied by GDP, GDP per capita, and GDP at Purchasing Power Parity (PPP) in different studies.

Therefore, we have added human capital especially in this configuration, and the functional form and estimable model is represented as:

$$lnCO_{2ij} = \alpha_{ij} + \beta_1 HC_{ij} + \beta_2 lnGDP_PC_{ij} + \beta_3 FossilEnergy_{ij} + \beta_4 lnEnergy_use_{ij} + \beta_5 T_{ij} + \mu_{ij} \quad (3)$$

In equation (3), 'i' and 'j' represent country and year respectively and β_1, β_2, β_3, β_4, and β_5 are the coefficients to be estimated which represent the rate at which the CO_2 emissions change as a result of change in the respective independent variables. Carbon dioxide (CO_2) is considered the prime measure of environmental degradation and it is the dependent variable used to measure the environmental degradation. HC is human capital, GDP_PC is real GDP per capita, FossilEnergy is the percentage of fossil energy in total energy consumption, Energy_use is the amount of energy used in per capita form, and T represents trade variable. The variables' definitions and measurement units are given in the section 5 below.

4. Econometric Methodology

For examining the interrelationship between CO_2 emissions and its macroeconomic causes for a panel of developing countries, this study follows a robust and modern multi-stage approach, termed as the "Large N, Large T" panel time series approach rooted in macro econometrics. Conventional panel data approaches such as Fixed Effects or GMM are not applied, as they are unable to address the three major issues associated with macro panel data namely non-stationarity, slope heterogeneity, and cross-sectional dependence (CSD).

4.1- Preliminary diagnostics: CSD and heterogeneous slope testing

Macro-panels are often observed with inter-dependencies, driven by factors such as global shocks, trade, and common policy regimes. In order to address the severe implications caused by such cross-sectional dependencies, firstly, we apply the Pesaran (2004, 2015) CD tests for the presence of Cross-sectional dependence (CSD) effects. Failure to address the CSD may result in biased results and spurious significance issues. Concomitantly, we check for the validity of the assumption of slope homogeneity. Considering the significant structural heterogeneity of the sampled panel of 55 nations, we apply the Pesaran and Yamagata (2008) and HAC-robust Blomquist and Westerlund (2013) tests for Slope Homogeneity.

4.2- Panel unit root and cointegration tests

The time series length of this study, T=53, warrants us to conduct Panel Unit Root tests and cointegration tests to make robust analysis. The study applied the Pesaran (2007) CIPS (cross-sectionally augmented Im-Pesaran-Shin) test, a second-generation unit root test accounting for CD by including cross-sectional averages in the Dickey-Fuller regression equation. We also check the unit roots with breaks using Karavias and Tzavalis (2014) test.

After establishing the integration of variables, that in our case is $I(1)$, we then continue to examine the presence of a long run equilibrium relationship, which is known as cointegration test. Westerlund (2005) cointegration test possesses better size accuracy and higher power as contrasted with the Pedroni (2004) residual-based test. To be sure, we employ these two different methodologies to arrive at our findings for cointegration:

i- Pedroni (2004): This is a residual-based approach, which tests for the stationarity of error terms. We estimate it using the 'demean' option in Stata for addressing the cross-sectional dependence.

ii- Westerlund (2005): This is an error correction-based approach, which tests whether error correction is statistically significant.

4.3. Causality analysis

The direction of the relationship is identified through the application of the Juodis et al. (2021) Granger Non-Causality Test (JKS). While the standard Granger Non-Causality Test merely employs an

Ordinary Least Squares approach, the JKS method uses a half-panel jackknife estimator, which guarantees unbiasedness even in panels with a medium time dimension, ensuring a causal link between the macroeconomic variables and CO_2 emissions.

4.4. Long-Run estimation: the DCCEMG, CCEMG, and AMG approaches

The main empirical model is specified using the estimator of Dynamic Common Correlated Effects (DCCE) by Chudik and Pesaran (2015), which copes with CSD by using the cross-section averages of the outcome variables (CO_2 emissions in our case) and independent variables. It also addresses the slope heterogeneity by using country-specific coefficients and averaging, and avoids the small sample time series bias (Nickell bias) using Recursive Mean Adjustment. Our approach uses a dynamic panel model to bridge the gap between immediate changes and long-term equilibrium. Moreover, the Augmented Mean Group (AMG) estimator is also presented for arriving at consistent estimates. In empirical panel data research, the AMG estimator is also applied as a substitute for the CCEMG estimator (Eberhardt & Bond, 2009b; Eberhardt & Teal, 2010). It is the CCEMG estimator attributed to Pesaran (2006) that addresses CSD, heterogeneous slope coefficients, and is robust to the structural breaks as well.

5. Variables, data and summary statistics

The panel data for this study consists of the 55 developing countries for which the data were available in annual observations from 1971 to 2023. As the data for HC, percentage of fossil energy, and per capita energy consumption were available till 2019, therefore a five-year moving average has been used for updating these two variables in the data. In our model, affluence is proxied by real GDP per capita at constant 2015 US$ in line with Yao et al. (2020), Khan et al. (2018) and Nathaniel et al. (2021), and technology is proxied by the energy consumption measured in kg of oil equivalent per capita that is in line with Sapkota and Bastola (2017) and Khan et al. (2018). In this study, CO_2 emission per capita is taken as outcome variable that is widely used in economic literature to represent environmental degradation such as in Yao et al. (2020), Khan et al. (2018) and Sapkota and Bastola (2017). In equation 4, the 'HC' represents human capital index (data taken from Penn World Table), the variable 'trade' (T) denotes the trade as percentage of GDP. The information about variables is briefly described in table 2 with their definitions and measurements.

Table 2. Variables and data source

Variables	Measurements	Data source
CO_2 emissions (CO_2)	Carbon dioxide (CO_2) emissions excluding LULUCF per capita (t CO_2e/capita)	World Development Indicators (WDI) online
Human Capital (HC)	Human Capital Index	Penn World Table
Affluence (GDP_PC)	GDP per capita (constant 2015 US)	WDI online
Fossil energy consumption (FossilEnergy)	Fossil fuel energy consumption (% of total)	WDI online
Energy use (Energy_use)	Energy use (kg of oil equivalent per capita)	WDI online
Trade (T)	Trade (% of GDP)	WDI online

Data Sources: Penn World Table 10.1 from the Groningen Growth Development Centre GGDC (2023) and Feenstra et al. (2015), and the World Development Indicators online.

5.1 Descriptive statistics

Table 2 represents the statistical summary and provides a general glance of whole data in detail, including carbon emission with its economic drivers such as GDP growth, energy use, fossil energy, human capital, and trade openness. The table 2 presents the summary statistics for the data as overall(general), between (inter country) and within (intra country). The overall calculations are obtained over the observations of 2915, between for 55 countries and based on 53 years.

Table 3. Summary statistics

Variable		Mean	Std. dev.	Min	Max	Observations
$lnCO_2$_PC	overall	0.35	1.22	-3.81	3.85	N = 2915
	between		1.16	-2.32	3.23	n = 55
	within		0.41	-1.14	2.21	T = 53
HC	overall	2.03	0.55	1.04	4.35	N = 2915
	between		0.41	1.30	3.27	n = 55
	within		0.37	1.09	3.79	T = 53
lnRGDP_PC	overall	8.09	1.07	5.69	11.14	N = 2915
	between		1.01	6.28	10.32	n = 55
	within		0.37	6.29	10.01	T = 53
FossilEnergy	overall	63.25	28.53	1.65	100.00	N = 2915
	between		27.66	8.38	99.90	n = 55
	within		7.92	23.38	93.13	T = 53
LnEnergy_use	overall	6.64	0.80	4.39	9.37	N = 2915
	between		0.76	4.91	9.03	n = 55
	within		0.28	5.20	7.41	T = 53
Trade	overall	70.75	57.16	0.02	442.62	N = 2915
	between		53.60	23.07	340.10	n = 55
	within		21.11	-42.19	240.24	T = 53

Source: Authors' calculation based on data

5.2 Correlation matrix

The correlation matrix represents the linear relationship among the variables. It shows that the value of correlation of $lnCO_2$ to HC and lnRGDP_PC is 0.535, and 0.838 respectively; while with FossilEnergy and lnEnergy_use are 0.828 and 0.886 showing strong association among carbon discharges and macroeconomic growth, FossilEnergy, and energy consumption. The correlation coefficient between $lnCO_2$_PC and Trade is 0.355 which is weak. The correlation among the independent variables is strong (0.848) only in case of lnRGDP_PC and lnEnergy_use, and mild in other cases (less than 0.7).

Table 4. Correlation matrix

	$lnCO_2$_PC	HC	lnRGDP_PC	FossilEnergy	lnEnergy_use	Trade
$lnCO_2$_PC	1.000					
HC	0.535	1.000				
lnRGDP_PC	0.838	0.639	1.000			
FossilEnergy	0.828	0.428	0.614	1.000		
lnEnergy_use	0.886	0.544	0.848	0.606	1.000	
Trade	0.355	0.330	0.463	0.274	0.378	1.000

Source: Authors' calculations based on data

6. Econometric pre-estimation diagnostics

Preliminary statistical analysis and diagnostics are conducted to verify the nature of the data and hence selecting the appropriate estimation strategy with good fit. The most important statistics in this section are CSD tests, Unit Root tests, and the slope homogeneity tests. Based on the results of these tests, we move on to the appropriate econometric model estimation.

6.1 Cross-sectional dependence Test

This study primarily utilizes the Pesaran (2004, 2015) CSD tests, which are applicable for dynamic heterogeneous panels and are known to be consistent. The following table presents the results of the Pesaran (2004) CD Test, under the H_0: Cross-section independence.

Table 5. Pesaran (2004) CD Test and Pesaran (2015) CSD Test

Variable	CD-test	p-value	corr	abs(corr)
$lnCO_2$_PC	109.59	.000	0.391	0.550
HC	272.03	.000	0.970	0.970
lnRGDP_PC	133.21	.000	0.475	0.638
FossilEnergy	34.42	.000	0.123	0.577
lnEnergy_use	115.65	.000	0.412	0.594
Trade	56.71	.000	0.202	0.349
Pesaran (2015) test for weak CSD				
H_0: errors are weakly cross-sectional dependent.	CD = 2.269	.023		

Source: Authors' calculations based on data

The results suggest that there is issue of CSD in the data as null hypothesis is rejected on the basis of p-values less than 0.05. The study also uses Pesaran (2015)[§] test for checking the weak cross-sectional dependence hypothesis. Typically, it is run as a post-estimation after running a panel regression model. In this routine, firstly the residuals are calculated and then the test is implemented on them. The calculated vale of test is 2.269, with the p-value of 0.023 that implies rejection of the null and we conclude that there is strong evidence of CSD. The confirmed detection of CSD in the data implies that we should use those estimations strategies such as CCEMG and AMG that are robust for cross sectional dependence.

6.2 Panel unit root tests

The panel unit root procedures that incorporate and address the cross-sectional correlation are known as second generation unit root tests. We have used the CIPS test developed by Pesaran (2007) is implemented in this research.

Table 6. CIPS & IPS unit root test estimation

Variable	Specification	CIPS (Levels)	CIPS (first difference)	IPS (Levels)	IPS (first difference)	Remarks
$lnCO_2$	Constant	−2.069∗	−5.951∗∗∗	−1.368∗	−42.716∗∗∗	*I*(1)
	Constant and Trend	-2.223	−6.168∗∗∗	-1.193	−42.950∗∗∗	
HC	Constant	0.092	-1.622	1.831	−9.063∗∗∗	*I*(1)
	Constant and Trend	-0.197	-2.241	1.97	−10.956∗∗∗	
lnRGDP	Constant	-1.666	−5.251∗∗∗	1.57	−31.515∗∗∗	*I*(1)
	Constant and Trend	-2.026	−5.457∗∗∗	-0.058	−31.541∗∗∗	
Fossil	Constant	−2.410∗∗∗	−6.114∗∗∗	−2.543∗∗∗	−43.189∗∗∗	*I*(0)
	Constant and Trend	-2.451	−6.352∗∗∗	-0.132	−42.367∗∗∗	
lnEnergy	Constant	−2.180∗∗	−5.969∗∗∗	−3.594∗∗∗	−41.673∗∗∗	*I*(1)
	Constant and Trend	-2.166	−6.170∗∗∗	0.104	−42.955∗∗∗	
Trade	Constant	-1.859	−5.963∗∗∗	−3.11∗∗∗	−43.826∗∗∗	*I*(1)
	Constant and Trend	-2.418	−6.114∗∗∗	−2.633∗∗∗	−41.98∗∗∗	

Source: Authors' calculations.

6.2.1 CIPS & IPS unit root test estimation

[§] It is run as xtcd2 in Stata after estimating the regression model

The results of CIPS unit root test with null hypothesis of non-stationarity are presented in Table 5. The IPS panel unit root test (built-in command in Stata 17 with demean option) is also applied here for being doubly sure of our findings. The results on these two panel unit root tests are reported in the table 5.

To determine the integration properties of the variables, we employ both the Im-Pesaran-Shin (IPS) test and the Pesaran (2007) CIPS test. The latter is specifically chosen to address potential size distortions caused by CSD. The results, presented in Table 5, indicate that while the variables exhibit unit roots in their levels—particularly when deterministic trends are incorporated—they become stationary in their first differences at the 1% significance level. Consequently, we infer that the all series follow an $I(1)$ process, providing a robust basis for the subsequent cointegration testing. It implies that dynamic models will have to be utilized for estimation of the model.

6.2.2 Karavias and Tzavalis unit root test with structural breaks

Structural breaks are another characteristic of panel econometrics particularly when T is large. In that respect, Karavias and Tzavalis (2014) devised unit root test which detects the structural break in the presence of CSD. This unit root test may be applied to identify the structural breaks in small and large time series in the panel. The null hypothesis is that all series in the panel are unit-root processes or non-stationary. The alternative is that some or all the series are stationary.

Table 7. Karavais & Tzavalis Unit root test estimation with structural breaks

	lnCO2_PC	HC	lnRGDP_PC	FossilEnergy	lnEnergy_use	Trade
Statistics	-0.144	-0.002	-0.033	-7.327	-0.037	-13.926
5% bootstrap critical values	-0.135	-0.002	-0.030	-6.547	-0.035	-12.629
p-values	.000	.000	.000	.000	.000	.000
Estimated breaks	1976	2002	1973	1986	1989	1973

Source: Authors' calculations.

As the calculated p-values are less than 0.05, therefore the null is rejected. The confirmation of structural breaks in the series necessitates that we should apply such estimation approaches that are also robust to such issues. For this purpose, we choose AMG, CCEMG and DCCEMG following the relevant empirical literature mentioned above.

6.2.3 Slope homogeneity test

CSD and slope heterogeneity are two main issues of panel data in relevant literature which may result in biased and inefficient estimations. Therefore, it is very essential to test for the presence of slope heterogeneity. For this purpose, the Pesaran and Yamagata (2008) test to check for the presence of slope heterogeneity is applied here.

Table 8. Results of Slope Homogeneity Tests

Test Specification	Δ(Delta)	p-value	Δ_{adj}	p-value
Pesaran & Yamagata (2008)	68.86	< .001	73.91	< .001
Blomquist & Westerlund (2013)[a]	48.73	< .001	52.31	< .001

Source: Authors' calculations based on data

Note. Δ and Δ_{adj} denote the Delta and Adjusted Delta statistics, respectively. H_0: Slope coefficients are homogenous. a. Results computed using a Bartlett kernel with an average bandwidth of 3 to account for heteroskedasticity and autocorrelation (HAC).

The null hypothesis (H_0) states that the slope coefficients are homogenous (identical) across all 55 countries. The calculated Delta & Adj. Delta values (68.86 and 73.91) are quite high, with p-values of 0.000 that means we reject this hypothesis. After using the Blomquist and Westerlund (2013), which

accounts for Heteroskedasticity and Autocorrelation (HAC), the conclusion of slope heterogeneity still holds.

These results confirm that the directional relationship between the chosen determinants and environmental degradation may not be the same among the 55 sampled nations. Therefore, the traditional pooled estimators that impose a single coefficient on all cross-sections would be biased. Consequently, this necessitates the use of Mean Group (MG)-based approaches such as CCEMG and AMG instead of pool estimators. These MG estimators can explicitly take into account the country specific slopes heterogeneity while providing a consistent estimate for all panels as well. CCEMG is also documented to have robust estimation in the presence of structural breaks.

6.2.4 Panel Cointegration tests

For this study, two different econometric frameworks were applied to comprehensively check the long-run equilibrium relationship among variables: the residual-based approach of Pedroni (2004); and the error-correction-based approach of Westerlund (2005) that is a LM-bootstrap cointegration test and takes the presence of CSD into explicit consideration and is considered as a second generation cointegration test.

Table 9. Results of Panel Cointegration tests

Test Framework	Hypothesis and Specification	Statistic	p-value
Westerlund (2005) †	H_A: Some panels are co-integrated		
	Panel Mean	–3.598	< .001
	Panel Mean + Trend	–3.699	< .001
	H_A: All panels are co-integrated		
	Panel Mean	-0.8513	0.1973
	Panel Mean + Trend	–3.750	< .001
Pedroni (2004) ‡	H_A: All panels are co-integrated		
(Trend not included)	Phillips–Perron t	–9.942	< .001
	Augmented Dickey–Fuller t	–8.851	< .001
(Trend included)	H_A: All panels are co-integrated		
	Phillips–Perron t	–9.880	< .001
	Augmented Dickey–Fuller t	–9.536	< .001

Source: Authors' calculations based on data

Note. H_0: No cointegration. All tests are specified with the removal of cross-sectional means (demean) to account for cross-sectional dependence. † Westerlund results report the Variance Ratio statistic. ‡ Pedroni results report the most robust statistics (PP and ADF) under the "panel specific cointegrating vector" specification.

Table 8 clearly demonstrates that both the methods indicate cointegration. Westerlund variance ratio statistics mainly rejects the null hypothesis of no cointegration, with just one exception in case of panel mean without trend. Similarly, Pedroni test results with highly significant ($p < .001$) Phillips, Perron and Augmented Dickey Fuller statistics also corroborate these findings. On the whole, these tests indicate that the considered variables exhibit a stable long run equilibrium interrelationship, which justifies the use of the DCCEMG and AMG model for estimation.

6.2.5 Granger causality test

The Granger non-causality test proposed by Juodis et al. (2021) is used in this study to identify the directional nature of the relationship. This approach departs from traditional panel causality tests by using a Half-Panel Jackknife (HPJ) estimator instead of a fixed-effects estimator that gives rise to Nickell bias, allowing for robust inference even in the 55 countries sample.

The HPJ Wald statistic is significant as indicated in Table 9 (46.17, $p < .001$) and gives a strong reason to reject the null hypothesis of non-causality. This implies that the covariates have a jointly significant causal impact on CO_2 emissions, therefore providing predictive validity for the estimated

model.

Table 10. Panel Granger Non-Causality Test Results (JKS, 2021)

Dependent Variable	HPJ Wald Statistic	p-value	Optimal Lags (BIC)
$lnCO_2$_PC	46.17***	< .001	3

Source: Authors' calculations based on data.

Note. H_0: Covariates do not Granger-cause $lnCO_2$_PC. The test employs the Half-Panel Jackknife (HPJ) estimator to correct for incidental parameter bias. Bootstrap variances are based on 200 iterations. Significance: *** p < .01.

7. Empirical results

After the application of diagnostic tests such as CSD test, Slope Homogeneity Test, Cointegration Tests, we need to deploy those estimation techniques which are suitable for heterogeneous panels exhibiting strong cross-sectional dependence and also exhibit some structural breaks. For this purpose, CCEMG, DCCEMG and specifically the AMG are preferable. Furthermore, CCEMG is also robust to the structural breaks as noted by Le (2016) and Guloglu and Bayar (2016).

Table 11. Results of estimated econometric models

Dep. Var: $lnCO_2$_PC	(1) DCCEMG	(2) CCEMG	(3) AMG
HC	-0.129	-0.132	-0.179***
	(0.672)	(0.376)	(0.000)
Trade	0.000819**	0.000291	0.000185
	(0.024)	(0.174)	(0.592)
FossilEnergy	0.0212***	0.0142***	0.0151***
	(0.000)	(0.000)	(0.000)
lnRGDP_PC	0.325***	0.347***	0.356***
	(0.000)	(0.000)	(0.000)
lnEnergy_use	0.456***	0.533***	0.679***
	(0.000)	(0.000)	(0.000)
L.$lnCO_2$_PC	-0.739***		
	(0.000)		
c_d_p			0.580***
			(0.000)
$lnCO_2$_PC_avg		0.805***	
		(0.000)	
lnRGDP_PC_avg		-0.347**	
		(0.048)	
HC_avg		0.142	
		(0.347)	
FossilEnergy_avg		-0.0177***	
		(0.006)	
Trade_avg		-0.000305	
		(0.680)	
lnEnergy_use_avg		-0.138	
		(0.441)	
Constant		-1.899**	-7.299***
		(0.047)	(0.000)
Observations	2750	2915	2915
	R^2=0.332, F(1045, 1705) = 3.28 p>F= 0.000	Wald $Chi^2(5)$ =233.36, p>Chi^2=0.000	Wald $Chi^2(5)$ =227.31, p>Chi^2=0.000
CD test	-1.01	0.76	0.16
	p = 0.312	p = 0.450	p = 0.873

Source: Authors' calculations based on data

Note: *p*-values in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. AMG and CCEMG use outlier-robust means.

The DCCE's figures reveal that the main reasons behind the CO_2 emissions in 55 countries include energy consumption and economic growth. In particular, lnEnergy_use (beta = 0.456, p <.001) and lnRGDP (beta = 0.325, p <.001), are two main variables capable of affecting positively the environmental degradation, and are highly statistically significant. Also, the share of fossil fuels in the energy mix is another major component pushing emissions (beta = 0.021, p <.001). While trade openness shows a somewhat positive impact but is hardly noticeable. And the human capital, on the other hand, cannot be said statistically to influence emissions under present specification (p =.672). The error correction term (ECT) as represented by the lagged dependent variable is not only negative but very statistically significant (beta = -0.739, p <.001), thereby serving as strong evidence of the quick return to equilibrium of the long-run. Similarly, CD test (p =.312) supports the fact that the model is able to deal well with dependence across different countries. The CCEMG based estimations also bring forth very similar results except that trade is not statistically significant anymore.

To check if the results are sensitive to the exact approach used to account for cross-sectional dependence, we also employed the AMG estimator that can be a substitute for CCEMG, as already mentioned. In contrast to the CCE approach, which ends up using cross-sectional averages as proxy for unobserved factors, the AMG estimator is able to extract a 'Common Dynamic Process', which corresponds to aggregation of common sources of global and environmental development over time. This enables a refined analysis for variables such as Human Capital that can be directly correlated to global trends of development.

More importantly, the issue of cross-section dependence and heterogeneous slopes is taken into account by means of the AMG Estimator. The results confirm that economic growth, fossil fuels, and total energy consumption are significant drivers of CO_2 emissions in the long run, whereas human capital has a statistically significant mitigating effect on environmental emissions. Trade openness, however, lacks any statistical significance in the long-run model. The statistical significance of the common dynamic process supports the evidence of global unobservable shocks that influence the sample countries included in our dataset.

The result achieved by means of the Augmented Mean Group approach represents a milestone in our study. Indeed, unlike what the previous results achieved by the application of CCE estimators, such as DCCEMG and CCEMG, which treat global shocks as "nuisance" effects to be removed, the AMG approach, as suggested by Eberhardt and Bond (2009a), treats global shocks as a Common Dynamic Process (CDP). Moreover, the Human Capital parameter turns out to be statistically highly significant that reduces the CO_2 emissions. In case of Human Capital (beta = -0.179, p = 0.000), unlike the DCCEMG and CCEMG models, the AMG model shows that for each 1-point rise in HC index, CO_2 emissions are reduced by 0.17%. This implies that when we account for the global "background" evolution of technology, education is a powerful mitigator of pollution. This may be attributed to the likely adoption of green technologies facilitated by higher human capital. The variables of energy use (.679) and GDP (.356) are still positive and highly significant, reinforcing the "dirty growth" narrative of the previous models. The Common dynamic process (denoted by c_d_p in table 10) coefficient is highly significant at 0.58. This is the "global unobserved trend" in emissions (technology shifts, global climate agreements). The AMG model's ability to account for this trend has allowed the specific impact of Human Capital to finally emerge. Last but not the least, the p-value of CD-Tests in all three models is also much larger than common threshold of 5%, leading us to conclude that the models have taken care of the CSD issues and results are robust and reliable.

8. Summary conclusions, policy recommendations, and areas for future research

This study is based on the effects of some core macroeconomic factors influencing the environmental degradation in developing countries (n=55) from all over the world over the period of 1971 to 2023. These core factors included affluence, technology, trade, and human capital. The main research question is related with the effect of human capital on carbon emissions in developing countries that as a group are emerging as a major source of such emissions. To address this question, this study applied various pre and post estimation econometric techniques including CSD test, unit root tests with and without structural breaks, slope homogeneity test, and cointegration test in modelling the impact of human capital and other factors on carbon emissions. The results of these tests indicate that we should apply those panel date econometric models that can address the cross-sectional dependence, slope heterogeneity, and possible structural breaks. Hence, the econometric modelling is conducted by using CCEMG, DCCEMG and AMG approaches that are applied to evaluate the impact of human capital, economic growth, and other factors on the carbon emissions. The estimated coefficients of the macroeconomic driving forces responsible for carbon emissions are approximately the same under all specifications. Fossil energy share in total energy, energy consumption per capita, and GDP per capita are statistically significant and positive contributors to CO_2 emissions across all specifications. Human capital appears as a negative contributor in all specifications but it is statistically significant in case of AMG only.

Three broad conclusions from the econometric models emerge. Firstly, economic growth and fossil fuels are "structural" pollutants. Secondly, human capital is a "latent" mitigator (it arises as significant only after the AMGs common dynamic process is used), and trade is a "transitory" element (significant only in the dynamic model). These results of this paper are more aligned and compatible with the works of various authors and researchers, such as Hao et al. (2021), Yao et al. (2020), Bano et al. (2018), and M. Khan (2020).

The results are very important for decision-makers in creating policies to reduce carbon pollution in the environment since pollution is not just a problem for one country or state but a problem for the entire world. The main factors that increase carbon emissions are GDP and energy consumption at high levels, with energy consumption being more elastic to CO_2 than GDP and trade for developing countries. This may be because they use cheaper and more environmentally harmful sources of energy, such as fuel or thermal coal.

Other sources of energy conversion to green that could be used in this association to satisfy the economic needs are the hydro power, solar energy and wind spinning. Green sources of energy are always clean and renewable; hence, the demands should be satisfied by using the sources of green energy. The positive aspect in the findings is that the relationship between the level of human capital and the environmental degradation is inversely related in developing countries since the greater the level of human capital, the less would be the amount of carbon emission. This significant conclusion is a powerful policy point of view to make an investment in education because it will have a direct effect on the behaviors, norms and habits of the people in the long term. The societies that have higher level of human capital are likely to produce and make use of green technologies owing to better know-how and awareness about severity of environmental challenges (Khan, 2020). Therefore, increasing the human capital should be suggested as national policy since it not only leads to economic growth but can even more effectively affect the quality of the environment.

For future research, the human capital can be explored further as to which component of human capital is more favorable for environmental protection. Similarly, the decoupling role of human capital can also be explored. Last but not the least, it is possible that the role of human capital in improving the

environmental outcomes may hinge upon the institutional variables which can be explored in case of developing countries as well.

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Annex-1

Table A1. The list of selected 55 developing countries included in this study.

Algeria	Argentina	Bangladesh	Benin
Bolivia	Brazil	Cameroon	Chile
China	Colombia	Congo Rep.	Costa Rica
Cote d'Ivoire	Dominican Republic	Ecuador	Egypt Arab Rep.
El Salvador	Gabon	Ghana	Guatemala
Honduras	Hong Kong	India	Indonesia
Iran	Iraq	Israel	Jamaica
Jordan	Kenya	Kuwait	Malaysia
Mauritius	Mexico	Morocco	Nepal
Nicaragua	Pakistan	Panama	Paraguay
Peru	Philippines	Saudi Arabia	Senegal
Singapore	South Africa	Sri Lanka	Sudan
Syrian Arab Republic	Thailand	Togo	Tunisia
Turkiye	Uruguay	Zimbabwe	