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How do economic growth, trade openness, and non-renewable and renewable energy affect environmental quality in VISTA Countries?

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Abstract

Purpose — This study examines the effects of economic growth, the use of renewable and non-renewable energy sources, and trade openness on carbon emissions in VISTA countries (Vietnam, Indonesia, South Africa, Turkiye, and Argentina)

Method — In this work, empirical methods include the second-generation unit root and cointegration tests, as well as Panel AMG and Panel CCE estimators.

Findings — The following are the key findings. First, the variables demonstrate a long-run relationship. Second, economic growth and the consumption of non-renewable energy sources contribute to an increase in carbon emissions over time, whereas the consumption of renewable energy sources lowers carbon emissions over time.

Implication — To promote sustainable growth in VISTA countries, it is recommended to increase investments in renewable energy sources while enhancing public sector supports for the private sector.

Originality — This is the first study to examine how economic growth, trade openness, and renewable and non-renewable energy sources affect carbon emissions in VISTA nations.

Keywords — VISTA countries, economic growth, trade openness, renewable and nonrenewable energy, carbon emissions.

Introduction

In an economy, when more goods and services are produced, there is a rising need for energy and a corresponding rise in energy consumption. Collectively, these challenges frequently raise the question of environmental sustainability. Sustainability refers to the necessity for a balance between environmental preservation and economic growth. Meeting present-day demands without jeopardizing those of future generations is the definition of sustainable development (Hossain et al., 2022; Todaro & Smith, 2020; WCED, 1987). Green growth must become a common practice if sustainable development is to be accomplished. The green growth strategy reduces greenhouse gas emissions and, consequently, carbon emissions protect biodiversity and lessen the danger of climate change. Additionally, this strategy directly impacts the life expectancy at birth. In this regard, a green growth strategy can raise welfare levels by promoting a high quality of life, a sustainable environment, and the need for clean energy.

Research into potential solutions and tactics to mitigate and regulate the adverse effects causing species extinction, global warming, climate change, food shortages, and environmental degradation is gaining more and more attention. It is impossible to overestimate the advantages of

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using energy and natural resources since it gives customers access to the products and services they want. However, this kind of consumption also generates greenhouse gases, such as carbon dioxide, which raises the earth's temperature and hastens the melting of glaciers. These changes in weather are unexpected and unpredictable. It also results in high rainfall and harsh droughts, destabilizing impacts (Balsalobre-Lorente et al., 2018; Suki et al., 2022). Institutions and organizations are attempting to adopt various actions to reduce the negative effects of natural resources and energy use and improve resource utilization. By switching from non-renewable to renewable inputs, innovating the existing infrastructure, and constructing clean manufacturing facilities at the lowest possible environmental cost, resource efficiency can be increased (Danish & Ulucak, 2020; Du & Li, 2019; Godil et al., 2021; Guo et al., 2018; Khan et al., 2022).

The VISTA countries (Vietnam, Indonesia, South Africa, Turkiye, and Argentina) are considered in this study. Although the countries that make up this group are not as large as China and India, they share a lot of traits. Most of these nations fall under emerging markets (Fornes & Philip, 2012). Their market is sizable, their workforce is youthful and expanding, their politics are stable, and their domestic consumption and energy demand are rising (Uyar & Gökçe, 2017). With regard to their gross domestic product sizes, Indonesia, Argentina, and Turkiye are among the top 20 economies (G-20).

This study analyzed the impact of non-renewable and renewable energy consumption, economic growth, and trade openness on carbon emissions in VISTA countries. The contribution of the present study to the literature is to determine the impact of growth, trade, and energy on the efforts of these five countries, which compete with developed countries, have large markets and young labor force, and attract attention with their growth rates, to improve environmental quality in the context of sustainable development. This study is different because no previous study on VISTA countries has been found in the literature review to determine the relationship between these variables. The first part of the study consists of an introduction and a literature review. The second section of the study presents the data set, descriptive information on the variables, and the empirical findings. The study concludes with a section on conclusions and recommendations.

The Environmental Kuznets Curve (EKC) theory created by Panayotou (1993) has shaped the scope of the relationship between economic growth and environmental quality. This theory contends that throughout the early stages of development, high income and economic growth take precedence over environmental consciousness. As income levels rise, environmental awareness rises, environmental laws are implemented, and there is a structural shift in favor of knowledge-intensive businesses and services. Better technology and greater environmental spending eventually lessen environmental degradation and pollution (Muhammad, 2019; Narayan et al., 2016; Odhiambo, 2012; Osadume & University, 2021; Pao & Tsai, 2011; Petrović-Ranđelović et al., 2020; Schröder & Storm, 2020; Song, 2021; Soytas & Sari, 2009; Yang et al., 2017); are only a few of the research that have examined the relationship between economic growth and carbon emissions. In addition to these studies, there are more and more being done on the causation relationship and cointegration between economic growth, trade openness, and carbon emissions (Alam & Murad, 2020; Cetin et al., 2018; Nurgazina et al., 2021; Ohlan, 2015). The argument that increased trade openness advances and accelerates environmental degradation is still being discussed in academic circles. Scale, technology, and composition have all been used to examine how trade openness affects the environment (Grossman & Krueger, 1991). The scale effect refers to the idea that higher CO_2 emissions result from increased energy consumption for higher production. Enhancing environmental quality through technology transfer and methods made available by new environmentally friendly technologies is known as the technical effect. The composition effect describes how, as income levels rise, the role of environmentally friendly services and IT-based industries in the economy grows (Chhabra et al., 2023).

The need for energy has also increased due to globalization, technological development, rapid population expansion, industrialization, and urbanization. Growing energy use and demand cause climate change and global warming, making sustainable development more difficult to comprehend. In this context, policies to reduce carbon dioxide emissions, which account for the largest portion of all greenhouse gas emissions (Shahzad et al., 2017), are a focus of intense global policymaking. As a result, the significance of renewable energy sources is growing daily. Using wind, solar, geothermal, and other renewable resources is encouraged as the reliance on fossil fuels is reduced. This is because such encouragement helps create a clean environment and reduce the negative consequences of global warming.

Many studies have concluded that economic growth and non-renewable energy consumption increase carbon emissions. Some of these studies have been conducted on a country-by-country basis (Ali et al., 2016; Amirnia, 2023; Mushtaq & Ahmed, 2021; Omri & Saadaoui, 2023; Shahbaz et al., 2013; Shahzad et al., 2017; Wen et al., 2021) and some on a country group basis (Akbar et al., 2024; Alola et al., 2019; Amin & Song, 2023; Godil et al., 2021). Studies on the impact of renewable energy consumption on carbon emissions and these variables have started to be widely included in the literature. The list below includes a few of these studies.

In accordance with the Environmental Kuznets Curve (EKC) Hypothesis, Zafar et al. (2019) examined the effects of non-renewable energy, renewable energy, and trade openness on CO_2 emissions for countries classified as emerging economies by Morgan Stanley Capital International (MSCI) between 1990 and 2015. The findings confirm the EKC hypothesis and demonstrate that the use of renewable energy has a negative impact on CO_2 emissions. Still, non-renewable energy and trade openness have a favorable impact.

In the European Union, Leitão & Lorente (2020) examined the connections between economic growth, trade openness, renewable energy, tourism receipts, and carbon dioxide emissions (EU-28) for 1995-2014. For long-run coefficient estimation, the fully modified ordinary least squares (FMOLS), panel dynamic ordinary least squares (DOLS), and generalized moments system (GMM-System) estimators are favored. The findings indicate that while trade openness, tourism receipts, and renewable energy sources reduce carbon emissions, economic growth increases them.

Usman et al. (2021) conducted a study spanning the years 1990–2017 to determine the success of financial inclusion, the use of renewable and non-renewable energy sources, and the reduction of ecological footprints for the 15 nations with the greatest emissions. The results demonstrate that while economic expansion and the use of non-renewable energy enhance environmental degradation, financial development, renewable energy use, and trade openness minimize it.

Ibrahim dan Ajide (2021) used the Environmental Kuznets Curve (EKC) Hypothesis and the parameters of technological advancement to examine the effects of renewable energy, non-renewable energy, and trade openness on environmental quality for the G-7 countries (Canada, France, Germany, Japan, Italy, USA, and the United Kingdom) for the period covering 1990-2019. Renewable energy reduces CO_2 emissions, whereas non-renewable energy and trade openness increase CO_2 emissions, according to the study where the existence of EKC was supported by empirical evidence.

Kim (2022) used the ARDL approach based on the Pooled Mean Group to analyze the effects of economic growth, trade openness, renewable energy (electricity) consumption, and information and communication technology use on CO_2 emissions for OECD nations based on the 1990-2018 timeframe (PMG). ICT use eventually leads to a rise in carbon emissions, although a tiny one. While consumption of renewable energy and trade openness are found to have a long-term reducing impact on carbon emissions, economic growth is found to raise CO_2 emissions both in the short and long term.

For the G-7 countries between 1990 and 2020, Wang et al. (2022) looked at the effects of trade openness, economic growth, renewable energy, technical innovation, and industrialization on ecological footprint. The CS-ARDL and AMG panel estimator approach was used in the study to make empirical estimations. Clean and renewable energy has been shown to lessen environmental pollution over the long and short terms. While technological innovation is found to boost environmental quality, trade openness, industrialization, and economic growth are found to reduce it over time.

Wen et al. (2022) investigate the effects of renewable and non-renewable energy consumption on carbon emissions. Annual data for African countries from 1990 to 2019 are used to calculate the cross-sectional autoregressive distributed model (CS-ARDL). Long-run coefficient estimation also employs the Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) estimators. The results demonstrate that over time, non-renewable energy sources, population growth, urbanization, trade opening, and economic growth all lead to a rise in CO_2 emissions, whereas renewable energy, foreign direct investment (FDI), and technical innovation lead to a decrease.

Usman et al. (2021) studied the effects of financial development, trade openness, economic growth, and renewable and non-renewable energy on Pakistan's carbon dioxide (CO2) emissions from 1990 to 2017 in 2022. The long-run results show that financial development and the use of renewable energy significantly improve environmental quality. In contrast, the use of non-renewable energy, economic growth, and trade openness significantly worsen it.

Suhrab et al. (2023) investigated the effects of urbanization, renewable energy, financial development, trade openness, and economic growth on CO2 emissions in Pakistan from 1985 to 2018. They discovered that while renewable energy reduces CO2 emissions, urbanization, financial development, and trade openness raise them.

Methods

This investigation uses panel data analysis to examine the effects of economic growth, trade openness, non-renewable energy consumption, and renewable energy consumption on carbon emissions in VISTA countries from 1990 to 2020. The following is a mathematical illustration of the study's model:

$$LnCO2_{it} = \beta_0 + \beta_1 LnEN_{it} + \beta_2 LnGR_{it} + \beta_3 LnREN_{it} + \beta_4 LnTO_{it} + \mu_{it} \quad (1)$$

The variables used in the analysis and explanations of these variables are presented in Table 1.

Table 1. Variables and Explanations

Variables	Explanation	Abbreviation
Carbon Emissions	(Kt)	$LnCO_2$
Non-renewable Energy Consumption	Non-renewable energy (Gigajoule GJ)	LnEN
Gross Domestic Product	GDP (Current US$)	LnGR
Renewable Energy Consumption	(% of total final energy consumption)	LnREN
Trade Opennes	(Import+Export)/GDP	LnTO

Sources: All data are from the World Bank, except for non-renewable energy consumption, which is from BP 2022.

In this paper, the suitable unit root test was applied in accordance with the results of the first test cross-sectional dependence test. Then, a co-integration test that considers the heterogeneity of slope coefficients was undertaken after a homogeneity test. Following the cointegration test, the strength (impact) of the long-run relationship is assessed using the AMG and CCE estimators.

Cross-Sectional Dependence Tests

In panel data analysis, the cross-sectional dependence of the series is tested first. This is because globalization speeds up interactions between nations, preparing the path for the fusion of their financial and commerce systems. Because of integration, a crisis or shock in one country may also impact other nations. The cross-sectional dependence test determines how other countries will be affected by a shock in one of the panel's member countries. Second-generation unit root tests are used if cross-sectional dependence is detected.

The literature suggests several tests to determine whether cross-sectional dependence exists. The Lagrange Multiplier (LM) test, created by Breusch and Pagan in 1980, is the first. This test is favored when the panel's cross-sectional size (NT) is less than its time dimension. This test's notation is as follows:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\mathcal{P}}_{ij}^{2} \quad (2)$$

Breusch and Pagan's (1980) LM test is not used when the cross-sectional dimension of the panel is equal to the time dimension (*N* = *T*) or the cross-sectional dimension of the panel is larger than the time dimension (*N* > *T*). Pesaran (2004) CD_{LM} test is used instead. The equation for this test is presented below:

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i+1}^{N-1} \sum_{j=i+1}^{N} \left(T_{\hat{\rho}_{ij}^2} - 1 \right) \tag{3}$$

LMadj, another method used to detect cross-sectional dependence, was developed by Pesaran et al. (2008) in response to the biased results of the LM and CDLM tests. This test can be used in both N > T and N < T cases. The notation of the LMadj test is as follows:

$$LM_{adj} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{v_{Tij}} \tag{4}$$

Hypotheses associated with the tests are as follows:
H_0: Cross-sectional dependence does not exist.
H_1: Cross-sectional dependence does exist.

Results and Discussions

Table 2 presents the results of the cross-sectional dependence test for the variables. According to the cross-sectional dependence test, all five series are significant since the probability value is less than 1%. Therefore, the null hypothesis is rejected. In other words, the existence of cross-sectional dependence in all five series is accepted. The cross-sectional dependence test for the model is also given in Table 3.

Table 2. Test of Cross-Sectional Dependence Test on the Variables

Test	$LnCO_2$		LnEN		LnGR		LnREN		LnTO	
	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
LM (Breush, Pagan 1980)	26.779	0.003*	28.756	0.001*	27.877	0.002*	37.471	0.000*	27.228	0.002*
CD LM (Pesaran 2004 CDlm)	3.752	0.000*	4.194	0.000*	3.997	0.000*	6.143	0.000*	3.852	0.000*
CD (Pesaran 2004 CD)	-3.978	0.000*	-3.876	0.000*	-3.014	0.001*	-3.479	0.000*	-3.802	0.000*
Lmadj (Pesaran vd. 2008)	11.417	0.000*	3.694	0.000*	6.667	0.000*	14.427	0.000*	7.889	0.000*

Not: *, **, *** represent %1, %5, %10 levels of significance respectively.

Table 3. Cross-Sectional Dependence Test Results on the Model

Test	PANEL	
	Statistic	Prob.
LM (Breush, Pagan 1980)	17.768	0.059***
CD LM (Pesaran 2004 CDlm)	1.737	0.041**
CD (Pesaran 2004 CD)	0.336	0.368
Lmadj (Pesaran vd. 2008)	5.037	0.000*

Not: *, **, *** represent %1, %5, %10 levels of significance respectively.

As seen in Table 3, the results obtained from the cross-sectional dependence test of the model are significant at 1%, 5%, and 10% significance levels. The significance of the model indicates that the null hypothesis is rejected, and therefore, there is cross-sectional dependence in the model. Second-generation panel unit root tests should be applied if cross-sectional dependence exists in the series. Therefore, the stationarity of the series will be tested with the CADF/CIPS unit root test, which is the second-generation unit root test.

Panel Unit Root Test

The Generalized Augmented Dickey-Fuller (CADF) test statistic developed by Pesaran (2007) is used to investigate whether the series contains unit roots. In this test developed by Pesaran (2007), lagged cross-sectional means of the ADF regression are also considered. After estimating the CADF unit root test, the CIPS statistic is averaged to determine whether the series is stationary.

The CIPS statistic, which is the simple arithmetic mean of the CADF test statistic, is calculated as follows (Yerdelen Tatoğlu, 2017):

$$CIPS\ (N,T) = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T) = \frac{\sum_{i=1}^{N} CADF_i}{N} \quad (5)$$

In equation (5), N is the cross-section size, T is the time dimension, and t_i (N, T) represents the i^{th} cross-section CADF statistic value. The hypotheses for this test are defined as follows.
H_0: There is a unit root (non-stationary)
H_1: There is no unit root (stationary)

Table 4. CIPS Unit Root Test Results by Levels

Variables	Form of test	CIPS İstatistic	Test Critical values		
			1%	5%	10%
Carbon	Constant	-1.577	-2.57	-2.33	-2.21
	Constant/Trend	-2.172	-3.10	-2.86	-2.73
Energy	Constant	-2.122	-2.57	-2.33	-2.21
	Constant/Trend	-2.475	-3.10	-2.86	-2.73
Growth	Constant	-1.327	-2.57	-2.33	-2.21
	Constant/Trend	-1.648	-3.10	-2.86	-2.73
Renergy	Constant	-1.107	-2.57	-2.33	-2.21
	Constant/Trend	-1.527	-3.10	-2.86	-2.73
Trade Opennes	Constant	-1.613	-2.57	-2.33	-2.21
	Constant/Trend	-2.901	-3.10	-2.86	-2.73

Note: *, **, *** represent %1, %5, %10 levels of significance respectively.

Table 4's CIPS test statistic values for each variable may be lower than their respective critical values (CIPS statistic Critical Value). These findings suggest that neither a constant nor constant trend can rule out the H_0 hypothesis. It demonstrates that the variables have unit roots, to put it another way. The first differences of the series were taken to guarantee stationarity. Table 5 displays the outcomes of the unit root tests with variations.

Table 5. CIPS Unit Root Test Results by Level of Difference

Variables	Form of test	CIPS İstatistic	Test critical values		
			1%	5%	10%
Carbon	Constant	-3.684*	-2.57	-2.33	-2.21
	Constant/Trend	-3.451*	-3.10	-2.86	-2.73
Energy	Constant	-4.181*	-2.57	-2.33	-2.21
	Constant/Trend	-4.116*	-3.10	-2.86	-2.73
Growth	Constant	-2.761*	-2.57	-2.33	-2.21
	Constant/Trend	-3.068**	-3.10	-2.86	-2.73
Renergy	Constant	-3.731*	-2.57	-2.33	-2.21
	Constant/Trend	-4.079*	-3.10	-.286	-2.73
Trade Opennes	Constant	-3.981*	-2.57	-2.33	-2.21
	Constant/Trend	-3.493*	-3.10	-2.86	-2.73

Not: *, **, *** represent %1, %5, %10 levels of significance respectively. Pesaran 2004, critical values are retrieved from pages 280- II b; 281 IIc.

As shown in Table 5, the CIPS statistic has a bigger absolute value than the critical values when all variables' initial difference CIPS statistic values are compared with those values (CIPS statistic>Critical Value). These findings show that the null hypothesis H_0 is rejected under both the constant and constant and trend conditions, and at the 1% significance level, all variables are stationary. Further evidence that the prerequisite for cointegration analysis is satisfied is that the series are $I(1)$ stationary in their first differences.

Homogeneity Test and Findings

The homogeneity or heterogeneity of the model's parameters plays an important role in selecting appropriate co-integration tests and estimation methods for the model. For this reason, homogeneity tests should be performed first to select the appropriate tests. Swamy $\hat{S}$, a Hausman-type test developed by Swamy (1970), is one of the first studies in the literature to test homogeneity. This test is used to test the homogeneity of slope coefficients. The notation of the Swamy $\hat{S}$ test is as follows (Yerdelen Tatoğlu, 2017):

$$\hat{S} = X^2_{k(N-1)} = \sum_{i=1}^{N}(\hat{\beta}_i - \bar{\beta}^*)' \hat{V}_i^{-1}(\hat{\beta}_i - \bar{\beta}^*) \tag{6}$$

In equation (6), $\hat{\beta}_i$ denotes the OLS estimators from the regressions by units, $\bar{\beta}^*$ denotes the weighted WE estimator, and $\hat{V}_i$ denotes the difference between the variances of the two estimators.

Pesaran and Yamagata (2008) improved and standardized the Swamy (1970) test. Thus, the Swamy (1970) test is first modified under slope homogeneity. Pesaran and Yamagata (2008) standardized the Delta test as (Δ). The notation of the modified test is as follows (Olowu et al., 2019):

$$\hat{S} = \sum_{i=1}^{N}(\hat{\beta}_i - \hat{\beta}_{WFE})' X_I' \frac{M_T X_i}{\tilde{\sigma}_i^2}(\hat{\beta}_i - \hat{\beta}_{WFE}) \tag{7}$$

In equation (4), $\hat{\beta}$ is the pooled OLS estimator, and beta hat sub cap *W* cap *F* cap *E* represents the weighted fixed-effect pooled estimator. *S* is the estimator. Thus, the Swamy test has been improved and contributed to the literature as the Delta (Δ) test. It is also accepted that this test yields better results.

The Delta ($\hat{\Delta}$) test developed by Pesaran and Yamagata (2008) is used for large samples. The representation of this test is given in Equation (5):

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\hat{S} - k}{\sqrt{2k}}\right) \tag{8}$$

The $\hat{\Delta}_{Adj}$ test statistics used for small samples is provided in equation (6):

$$\hat{\Delta}_{Adj} = \sqrt{N}\left(\frac{N^{-1}\hat{S} - E(\tilde{z}_{iT})}{\sqrt{Var(\tilde{z}_{iT})}}\right) \tag{9}$$

Provided that $E(\tilde{z}_{iT}) = k$, $Var(\tilde{z}_{iT}) = \frac{2k(T-k-1)}{(T+1)}$, N is the cross-sectional dimension in the equation. $\hat{S}$ is the Swamy dispersion test statistics. K represents the number of regressors/number of explanatory variables. $var(\widetilde{z_{iT}})$ refers to standard error. The hypotheses of this test are as follows:

H_0: $\beta_i = \beta$ slope coefficients are homogenous.
H_1: $\beta_i \neq \beta$ slope coefficients are not homogenous.

As a result of the analysis, if the test probability value is greater than 0.05, H_0 cannot be rejected, and it is accepted that the co-integration coefficients are homogeneous. However, if the test probability values are less than 0.05, the H_0 hypothesis is rejected, and it is concluded that the co-integration coefficients are heterogeneous.

Table 6. Delta Homogeneity Test Results

Test	Test Statistics	Probability
Δ	9.166	0.000*
Δ_{adj}	10.169	0.000*

Not: *, **, *** represent %1, %5, %10 levels of significance respectively.

According to the Delta test results in Table 6, the $\tilde{\Delta}$ and $\hat{\Delta}_{Adj}$ test statistics indicate that the H_0 is rejected at the 1% significance level for the constant term and training coefficients. This result implies that the slope coefficients in the model are heterogeneous.

Panel Cointegration Test Analysis

Cointegration analysis allows testing the long-run relationship of variables. This study uses the LM bootstrap panel cointegration test derived by Westerlund and Edgerton, which considers cross-sectional dependence and heterogeneity. The notation of this cointegration test is as follows (Westerlund & Edgerton, 2007):

$$LM_N^+ = \frac{1}{NT^2} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{\omega}_i^{-2}\, s_{it}^2 \quad (10)$$

In this equation, T denotes time frame; N refers to sample dimension; s_{it}^2 represents the sum of the error terms; $\widehat{\omega}_i^{-2}$ points to the variance of the error terms in the long term. Hypotheses on the test are provided below:
H_0: There is cointegration between variables (Bootstrap p-value >0,05).
H_1: There is no cointegration between variables (Bootstrap p-value <0,05).

If the Bootstrap p-value is larger than the significance level (%1, %5, %10), H_0 cannot be rejected. If the Bootstrap p-value is smaller than the level of significance (%1, %5, %10), H_0 is rejected.

Table 7. Lm Bootstrap Cointegration Test

Conditions	LM Statistics	Bootsrap p-value	Asymp p-value
Constant	1.273	1.000*	0.102
Constant and Trend	4.287	0.998*	0.000

Note: * and **represent %1 and %5 significance levels, respectively. The bootstrap is based on 10.000 replicants.

The results of the LM bootstrap cointegration test, which demonstrates the long run cointegration connection between the variables, are shown in Table 7. The bootstrap p-value is considered in cases of cross-sectional dependence and heterogeneity. According to the findings, the bootstrap test statistic's p-value is higher than 0.05. Therefore, it is impossible to rule out the null hypothesis, which states a cointegration relationship between the variables (Bootstrap p-value >0.05). Therefore, it is determined that the model's variables for carbon emissions, trade openness, energy consumption, economic growth, and renewable energy consumption have a long-term link and will move in concert throughout time.

Co-Integration Estimators and Results

In the presence of a cointegration relationship between the series, different estimators are used to measure the degree of impact of this relationship. In this study, the Common Correlated Effect (CCE) estimator and Augmented Mean Group (AMG) estimator proposed by Pesaran (2006) are used to measure the degree of influence of the long-run relationship. The panel CCE estimator can be used when the series are non-stationary at level, there is cross-sectional dependence, slope coefficients are heterogeneous, and there is a long-run relationship between the series. Moreover, this estimator also provides reliable results when the cross-sectional dimension is larger than the time dimension (N>T) (Pesaran, 2006). As an alternative to the CCE test, Bond and Eberhardt (2013) and Teal and Eberhardt (2010) developed the "Augmented Mean Group Effect (AMG)" estimator. It calculates the long run cointegration coefficients for the entire panel by weighting the arithmetic mean of the co-integration coefficients of the cross-sections. In this respect, the AMG estimator obtains more robust and reliable results than the CCE estimator. The AMG estimator is defined as a two-stage process. The first stage/step for the AMG estimator is defined below.

$$\Delta_{y_{it}} = \alpha_i + b_i \Delta x_{it} + c_i f_t + \sum_{t=1}^{T} d_t\, \Delta D_t + e_{it} \quad (11)$$

In Equation 11, Δ refers to the differential process, and D_t represents the time coefficient. In the second stage, the slopes of each unit are evaluated. The second step representation of the AMG estimator is as follows:

$$\hat{b}_{AMG} = N^{-1}\sum_{i=1}^{N}\hat{b}_i \quad (12)$$

The observables are represented by y_{it} and x_{it}, while f_t and $\hat{b}_{AMG}$ are the unobserved common factor and the AMG estimator, respectively.

Table 8. AMG and CCE Test Results

Dependent Variables	Augmented Mean Group (AMG)		Commen Correlated Effects Mean Group (CCE)	
	Coefficients	t-statistics	Coefficients	t-statistics
Energy	0.451*	4.00	0.284***	1.79
Growth	0.485*	3.96	0.322**	2.25
Renergy	-0.192*	-4.63	-0.228*	-3.65
Trade Opennes	0.029	1.20	-0.033	-0.71

Note: *, **, *** represent %1, %5, %10 levels of significance respectively.

Table 8 displays the panel co-integration estimator findings for the entire model using the AMG and CCE estimators. The coefficients of LnEN, which stands for Non-Renewable Energy Consumption, LnGR, which stands for Gross Domestic Product, and LnREN, which stands for Renewable Energy Consumption, are statistically significant and in line with theoretical expectations, according to both AMG and CCE estimators. Trade Openness, or LnTO, is consistent with theoretical predictions but is not statistically significant. According to the findings, a 1% rise in gross domestic product increases carbon emissions by around 0.49 %, a 1% increase in non-renewable energy consumption increases carbon emissions by about 0.45 %, and a 1% increase in renewable energy consumption decreases carbon emissions by about -0.19 %. As can be seen, a 1% increase in non-renewable energy consumption and gross domestic product increases carbon emissions, while a 1% increase in renewable energy consumption decreases carbon emissions.

Conclusion

In recent years, the use of fossil fuels has increased dramatically because of the rapid economic growth in developing nations. This has increased carbon emissions, substantially worsening ecosystem deterioration and environmental quality. This circumstance demonstrates the necessity for a new paradigm to stabilize the link between environmental harmony and economic growth.

By examining the effects of economic growth, trade openness, and non-renewable and renewable energy consumption on CO_2 emissions for the VISTA group nations from 1990 to 2020, this study seeks to contribute to the literature. First, the study's series and model are subjected to a cross-sectional dependence test. Cross-sectional dependence necessitated the adoption of second-generation panel unit root tests CADF and CIPS. To assess the cointegration connection, Westerlund and Edgerton's (2007) LM bootstrap panel cointegration test is chosen after testing the homogeneity-heterogeneity of the slope coefficients. Long-run coefficient estimation employs the AMG and CCE estimators. According to the theoretical support and literature assessment, economic growth and non-renewable energy use both worsen environmental quality in these nations by raising CO_2 emissions. In contrast, using renewable energy improves environmental quality by lowering CO_2 emissions. The results of some studies (Ibrahim & Ajide, 2021; Usman et al., 2021, 2023; Wen et al., 2022; Zafar et al., 2019), indicate that economic growth and non-renewable energy consumption increase carbon emissions, while renewable energy consumption reduces carbon emissions, support the findings of the current study.

The study is significant since it demonstrates how renewable energy lowers CO_2 emissions in VISTA group nations. In this respect, it would be significant for state institutions to support the private sector's development of renewable energy infrastructure and introduce financial instruments enabling investment opportunities to improve environmental quality. Additionally, these economies will benefit from policymakers' support of R&D to create new ecologically friendly technologies. Additionally, it will be crucial to conduct research to educate the nation's populace about green growth and the commercial sector about environmentally friendly production methods.

Naturally, our study has some of the same drawbacks as academic investigations. Due to data restrictions and a lack of observations, the study's most obvious shortcoming is that it does not span a larger time period. Policymakers will benefit from future studies that isolate the non-renewable and renewable energy mix into its component parts and analyze each one's effect on carbon emissions independently, as well as from their significant contribution to the literature.

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