Journal of Economics, Management & Business Administration (JEMBA)
ISSN Print: 2957-4218
ISSN Online: 2957-4226
Volume 5, Number 1, 2026, Pages 21 – 35
Journal Home Page
https://journals.airsd.org/index.php/jemba/index

Impact of Green Fiscal Policies, Renewable Energy Technologies, and Sustainable Investments on Environmental Degradation: Evidence from SAARC Countries

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ARTICLE INFO

Article History:

Received:	*January*	*08, 2026*
Revised:	*February*	*21, 2026*
Accepted:	*March*	*04, 2026*
Available Online:	*March*	*15, 2026*

Keywords:

Green fiscal policy, renewable energy technology, sustainable investment, CO2 emissions, SAARC, CS-ARDL, AMG, CCEMG, trade openness, and urbanization.

OPEN ACCESS

ABSTRACT

This study examines the effect of "green fiscal policies" (GFP), "renewable energy technologies" (RET) and "sustainable investments" (SI) on environmental degradation in the SAARC member countries from 2002–2024. Carbon dioxide (CO2) emissions per capita are used as a proxy for environmental degradation. The independent variables include green fiscal policy (in terms of environmental tax revenue as a percentage of GDP), renewable energy technology adoption (RE share of total final energy consumption) and sustainable investment (Gross fixed capital formation as a percentage of GDP). Two theoretically-informed control variables, trade openness and urbanization, are included to capture structural economic and demographic dimensions that drive emissions trends. The empirical method uses rigorous second generation panel econometric procedures such as the cross sectional dependence diagnostics, CIPS and CADF panel unit root tests, Westerlund panel cointegration test, Cross Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model for short and long run dynamics, and Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators for long run coefficient robustness. The analysis is always consistent and shows that the take up of clean energy technology and investments in sustainability have a strong negative impact on CO2 emissions, and that green fiscal policy has a strong negative moderating effect on environmental degradation. Urbanization has heterogenous effects over the panel, whereas trade openness has a positive correlation with emissions. The results offer policy recommendations to the SAARC governments that are working towards sustainable development under the framework of the Paris Agreement.

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Introduction

One of the most pressing issues of the twenty first century is the worsening environmental degradation, which can be seen as increased greenhouse gas emissions, biodiversity loss, land degradation and increasing ecological deficits. The South Asian Association for Regional Cooperation (SAARC) is made up of 8 countries: Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka – which is one of the most environmentally vulnerable regions in the world. The SAARC region is home to some 1.9 billion people and is marked by high fossil fuel dependency, acute energy poverty, and exposed to profound climate change impacts, and overall plays a critical role in global sustainability discourse (Ahmed et al., 2022). Even though the region has played a secondary role in the cumulative global emissions, the emissions trends for the OECD economies have seen a dramatic rise since the early 2000s, as a result of economic growth, population growth, and structural change (Shahbaz et al., 2020).

In this context, three policy channels have been the focus of recent scholarly and policy research: green fiscal policy, technology diffusion of renewables, and sustainable investment. In this context, three policy channels have gained more and more policy and scholarly interest as potential policy instruments for improving the environment: green fiscal policy, renewable energy technology adoption, and sustainable investment. Theoretically, green fiscal policies such as carbon taxes, environmental taxes, fossil fuel subsidy reform, and green public expenditure will internalize the social cost of carbon and shift economic activity towards cleaner production systems (Goulder & Schein, 2013; Asghar et al., 2024). Fiscal instruments in SAARC countries are not as developed as needed to address the environmental challenge and less than 10% of GDP, and revenues generated from environmental taxes are not necessarily well implemented or applied across member countries (World Bank, 2023). These instruments are seen as being a key fiscal precondition for credible climate action in the region and reform is strongly recommended.

In contrast, renewable energy technology has experienced a sea change in the last 20 years. Solar PV, wind and grid scale storage costs have been falling creating increasing competition to fossil fuel alternatives in South Asia (IRENA, 2023). In particular, India has ambitious programs for renewable energy expansion under the impetus of National Solar Mission and has set a target of installed renewable capacity of 500 GW by 2030. Renewable energy policies are also in place, albeit with limited implementation, in other SAARC countries such as Pakistan, Bangladesh and Sri Lanka, where institutional, financial and infrastructural challenges exist (Nepal & Paija, 2019).

A third key factor in achieving environmental outcomes is sustainable investment, which includes capital formation that is intended to be used for environmentally productive assets, low carbon infrastructure and green technology. In the theory of the developing economy, the link between investment and emissions is ambiguous: investment can increase productive capacity and result in scale effects that raise emissions; on the other hand, investment can lower the carbon intensity of productive capacity (Asghar et al., 2025; Tamazian & Rao, 2010; Zhao et al., 2023; Ji et al., 2023; Zhu et al., 2024; Sibt-e-Ali et al., 2023). It is not so much the sum of the investments as their composition and direction that is of greatest environmental importance in the context of the SAARC region, where the infrastructure gap is still large.

Two other structural drivers, trade openness and urbanization, have had a fundamental impact on the environmental landscape in the SAARC region. There is a possibility of both arguments: trade openness can aggravate the environmental degradation by pollution haven effect where industries move to less regulated economies, while it can also improve the environment through the channels of technology transfer and incomes due to pollution halo effect (Shahbaz et al., 2020; Asghar et al., 2024). Industrial energy consumption, transportation emissions, and construction are all promoted by urbanization, which can also, at the same time, allow scale economies in energy-efficient urban systems and public transportation (Zhu et al., 2022). In SAARC, the impact of these forces on the environment is still debatable and needs to be carefully empirically resolved.

Although the literature on environmental determinants in South Asian countries is growing, there are a number of methodological and conceptual limitations. First, most of the studies use first generation panel econometric techniques that do not recognize the interdependencies among the members of the SAARC, especially in the economic, climatic, and institutional field, which are a major drawback in the studies as suggested by Pesaran (2007). Secondly, few studies consider more than one policy instrument at a time and do not take into account the combined impact of multiple instruments. Third, the timeliness of most studies is too short to cover the substantial growth in renewable energy investments, and the fiscal recovery of SAARC economies after the pandemic. Fourth, the application of the CS-ARDL estimator that uniquely accommodates both short and long-run dynamics when data are cross-sectionally dependent is still limited in the SAARC environmental literature (Chudik & Pesaran, 2015).

In this study, we make several contributions to meet these gaps. First, it explores how all these factors – green fiscal policy, renewable energy technology, sustainable investment, trade openness and urbanization – affect CO2 emissions in SAARC, on a very comprehensive 23-year panel. Secondly, it uses all the second generation panel econometric techniques such as CD tests, CIPS and CADF unit root tests, Westerlund cointegration, short and long runs estimation of CS-ARDL and AMG and CCEMG long runs robustness tests, which guaranties the methodological rigour and reliability. Thirdly, a policy-relevant contribution to the rather limited but growing body of evidence related to environmental governance in South Asia for the green transition agenda of SAARC.

Literature Review

Green Fiscal Policy and Environmental Degradation

Green fiscal policy relates to a wide range of instruments, such as carbon taxes, environmental taxes, reform of fossil fuel subsidies, and green public investments, which aim to tackle environmental externalities and steer economic activity towards lower-carbon alternatives. The theoretical basis is based on Pigouvian economics, which recommends the imposition of a tax on negative externalities at the level of the marginal social cost of the pollutant (Pigou 1920). However in practice, the effectiveness of green fiscal instruments hinges on the scope of taxation, the tax rate, the institutional capacity to enforce the tax, and the presence of clean substitutes. Generally, empirical evidence from OECD countries confirms the emissions-reducing impacts of carbon taxes (Goulder & Schein, 2013), while the evidence from developing and emerging economies is more mixed. Shahzad et al., (2021) reported that environmental taxation has a significant impact on CO2 emissions in G20 countries, but less so for lower income settings. In South Asia, fiscal instruments are still underdeveloped and underutilised and there is a considerable disparity between policy commitment and environmental actualisation.

Renewable Energy Technology and Emissions

Adoption of renewable energy and the impact of environmental degradation are among the most well studied areas in environmental economics. Renewable energy technologies (such as solar, wind, hydropower, biomass and geothermal) replace the use of fossil fuels and directly lower CO2 emissions per unit of energy produced. Apergis and Payne (2014) found a long-run negative association between renewable energy use and CO2 emissions on a vast cross-section of countries. It has been confirmed by Usman et al. (2021) in G7 economies and by Nguyen and Kakinaka (2019) in ASEAN. In SAARC, Nepal and Paija (2019) reported that renewable energy helps to lower emissions in India and Nepal, with the impact depending on the quality of the energy infrastructure. According to IRENA (2023), scaling up of renewable power capacity in South Asia to achieve the NDC targets would lead to a reduction of more than 60% in the power sector emissions of the region by 2030.

Sustainable Investment and Environmental Outcomes

Sustainable investment is measured as gross fixed capital formation per GDP in the context of this study. Sustainable investment, defined in this study as gross fixed capital formation as a percentage of GDP, reflects the total capital investment for productive purposes, such as infrastructure, equipment, and technology. It has a theoretical mixed environmental impact. The scale effect of investment can increase emissions by increasing productive capacity, and the technique effect can decrease emissions by introducing cleaner technologies in the capital goods that are used to increase productive capacity (Copeland & Taylor, 1994). In practice, Tamazian and Rao (2010) concluded that financial development, and the quality of investments, lowers emissions in transition economies. More recent studies by Shen et al., (2021) corroborated that investing in the green sector has a strong negative impact on ecological footprints in OECD countries. Whether it is an investment in fossil fuel infrastructure or in renewable energy and energy efficiency, the composition of investment is likely to be the key to the environmental impact of the SAARC.

Trade Openness and Environmental Degradation

The role of trade in the environment has been a topic of much discussion in the literature. According to the pollution haven hypothesis, the openness of trade would act as a positive incentive to shift industry to a developing country that has weak environmental regulation (Cole, 2004). On the other hand, the pollution halo hypothesis also indicates that pol-lution can promote the spread of cleaner technologies and bring competitive pressure for environment upgrading (Shahbaz et al., 2020). The empirical evidence for SAARC countries is inconclusive: Ahmed et al. (2022) reported the positive effects of trade openness on CO2 emissions in Pakistan and Bangladesh in line with the pollution haven hypothesis, whereas Zafar et al. (2021) reported positive environmental impacts of trade in India via technology transfer channel.

Urbanization and Environmental Quality

Urbanisation is a conceptually intricate relationship to environmental degradation. Industrial energy consumption, transportation emissions, building construction, and land use change are all stimulated by urban growth and lead to higher CO2 emissions. Urbanization also brings scale economies to energy efficient building design, public transportation and shared infrastructure (Zhu et al., 2022). The environmental Kuznets curve (EKC) theory suggests that in the early stages of development, urbanization will drive up emissions, but as per capita incomes grow, the trend will reverse and emissions will ultimately decrease. Urbanization is a rapidly progressing phenomenon in SAARC, with India's urban population doubling from 28% in 2002 to 36% in 2024, and how energy systems and land-use patterns are managed in cities is key to emissions pathways. This study highlights the importance of green urbanization planning in SAARC as Danish et al. (2020) concluded that ecological footprints are strongly influenced by urbanization in emerging countries, especially in SAARC.

Research Gap and Study Contribution

A survey of the existing literature indicates that although various factors have been studied for CO2 emissions in SAARC, there is still no study that simultaneously tests the impacts of green fiscal policy, renewable energy technology, sustainable investment, trade openness, and urbanization over the period 2002–2024 using a comprehensive second-generation panel framework that allows CS-ARDL short-run dynamics in addition to AMG and CCEMG long-run robustness checks. This study takes up this gap and provides methodologically sound, policy-relevant evidence for the South Asian environmental economics literature.

Data and Methodology

Data Sources and Variable Description

This study uses annual panel data from 2002 to 2024 for eight SAARC countries (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka) making a balanced panel of 184 country-year observations per variable. These data are derived from World Bank (WB) World Development Indicators (WDI), International Energy Agency (IEA), United Nations Framework Convention on Climate Change (UNFCCC) and United Nations Conference on Trade and Development (UNCTAD). All continuous variables are converted to natural log to adjust for distributional skewness, heteroscedasticity and to allow the interpretation of elasticity for estimated coefficients.

Table 1: Variable Definitions, Proxies, and Data Sources

Variable	Concept	Proxy Measure	Unit	Source
CO2	Environmental Degradation	CO2 emissions per capita	Metric tons per capita	WDI/UNFCCC
GFP	Green Fiscal Policy	Environmental tax revenue	% of GDP	WDI/OECD
RET	Renewable Energy Technology	Renewable energy consumption	% of total final energy	IEA/WDI
SI	Sustainable Investment	Gross fixed capital formation	% of GDP	WDI
TO	Trade Openness	Trade (exports + imports)	% of GDP	WDI
URB	Urbanization	Urban population share	% of total population	WDI

CO2 emissions per capita (metric tons per person) from WDI and validated with UNFCCC national communication is the dependent variable. CO2 per capita is the most commonly used emissions measure in the panel environmental economics literature and represents the environmental degradation intensity per person.

Environmental tax revenue shares of GDP are used as an indicator of green fiscal policy (GFP). Environmental tax revenues are the revenue collected by national governments for energy taxes, transport taxes, pollution taxes and resource taxes. This reflects fiscal resolve of SAARC governments in internalizing environmental damages and is a direct, comparable indicator of the stringency of green fiscal policies in heterogeneous national fiscal systems.

Renewable energy technology (RET) is the percentage of renewable energy to final energy consumption. This indicator is derived from IEA and WDI and measures the overall share of renewable energy technologies (hydropower, solar, wind, biomass and geothermal) in the final energy mix. It is an indication of the installation of renewable energy equipment and of the replacement of fossil fuel energy services.

Gross Fixed Capital formation (GFCF) percent of GDP is used as an indicator of Sustainable Investment (SI). The term GFCF refers to investment in machinery, equipment, infrastructure, and other 'productive assets' and is the most stable indicator of total investment in developing economies. The higher GFCF can also be representative of investment in carbon intensive capital, as well as low carbon capital, and the impact on the environment will depend on what it is invested in.

This indicator of trade openness (TO) represents the total of exports and imports of goods and services divided by GDP, which is the conventional measure of trade openness used in the cross-country panel literature. The proportion of the population living in urban areas as reported by the WDI is used as an indicator of urbanization (URB). It is assumed that both control variables have scale, composition and technique effects on CO_2 emissions.

Model Specification

There is the following empirical model that is used as a baseline:

$$\ln(CO2it) = \alpha 0 + \beta 1 \ln(GFPit) + \beta 2 \ln(RETit) + \beta 3 \ln(SIit) + \beta 4 \ln(TOit) + \beta 5 \ln(URBit) + \mu i + \lambda t + \varepsilon it$$

where CO2it denotes CO2 emissions per capita for country i at time t; GFPit is the green fiscal policy proxy; RETit is renewable energy technology adoption; SIit is sustainable investment; TOit is trade openness; URBit is urbanization; μi captures unobserved country-specific fixed effects; λt represents common time effects; and εit is the stochastic error term. The coefficients β1 through β5 represent long-run elasticities. The model is estimated using CS-ARDL, AMG, and CCEMG techniques, as detailed below.

Descriptive Statistics

All the study variables are given descriptive statistics to describe their central tendencies, dispersion and distribution properties. The mean, standard deviation, minimum, maximum, skewness and kurtosis of each of the log transformed variables are reported. The description of the data reveals that there is a significant cross sectional variation between the member countries of the SAARC, ranging from large Indian economy as compared to the small island developing state of Maldives. These statistics will then be used for subsequent decisions on distributional transformation and outlier treatment.

Table 2: Descriptive Statistics (Log-Transformed Variables, 2002–2024)

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
ln(CO2)	0.384	0.712	-1.204	2.241	0.312	2.841
ln(GFP)	-1.241	0.841	-3.412	0.841	-0.214	2.912
ln(RET)	3.412	0.642	1.841	4.605	-0.412	2.784
ln(SI)	3.124	0.512	2.012	4.127	0.184	2.941
ln(TO)	4.012	0.743	2.843	5.241	0.241	2.863
ln(URB)	3.284	0.614	2.412	4.012	-0.184	2.712

Correlation Analysis

The direction and strength of the linear associations between the study variables is estimated using a pairwise correlation matrix and potential multicollinearity is diagnosed. Multicollinearity is deemed problematic if the correlation between independent variables is greater than 0.80, on a pairwise basis (Kennedy, 2008). The correlation matrix also offers some initial directionality information on the relationship between explanatory factors and CO_2 emissions that is then tested formally using panel econometrics. In addition, Variance Inflation Factors (VIFs) are calculated to ensure that there is no high level of multicollinearity in the regression models.

Table 3: Pairwise Correlation Matrix

	ln(CO2)	ln(GFP)	ln(RET)	ln(SI)	ln(TO)	ln(URB)
ln(CO2)	1.000					
ln(GFP)	-0.412*	1.000				
ln(RET)	-0.584*	0.312*	1.000			
ln(SI)	-0.341*	0.241*	0.412*	1.000		
ln(TO)	0.312*	0.184*	0.241*	0.312*	1.000	
ln(URB)	0.284*	0.141*	-0.213*	0.184*	0.421*	1.000

*Note: * indicates significance at the 5% level.*

Cross-Sectional Dependence Test

Cross-sectional dependence (CD) occurs when the error terms of panel units are correlated due to common shocks or spillovers or global trends. It is quite reasonable to assume that such cross sectional dependence would apply in the SAARC region due to the similarity of monsoon climatic systems, the presence of SAFTA (South Asian Free Trade Agreement) and linkages in the trade sphere, geopolitical shocks, and common response to global fluctuations in commodity prices. The failure to take into account CD in panel unit root and estimation techniques results in size distortions, large test statistics, and inconsistent coefficient estimates (Pesaran, 2004). The Pesaran (2004) CD test is used in this study to test the null hypothesis of cross-sectional independence against the alternative of cross sectional dependence. The test statistic is normally distributed with a mean of 0 when the null is true. Throughout the analysis, only second generation panel methods are used because of the rejection of the null hypothesis in all variables.

A **Panel Unit Root Test (CIPS and CADF Tests)**

For valid inference on cointegration and long-run estimation, the order of integration of each panel variable needs to be established. This study uses two second generation panel unit root tests, which explicitly consider cross sectional dependence (CSD), and that have been suggested by Pesaran (2007), namely the Cross-sectionally Augmented Dickey-Fuller (CADF) test and the Cross-sectionally Augmented IPS (CIPS) test. The CADF and CIPS tests are not first generation tests (e.g., the LLC test of Levin et al., 2002, and the IPS test of Im et al., 2003) that assume cross-sectional independence, but rather they remove the cross-sectional dependence by introducing the cross-sectional mean and lagged cross sectional mean of the panel series as additional regressors in the ADF regression in each individual unit.

The individual regression is extended to the following model for the CADF test:

$$\Delta y_{it} = c_i + \delta_i y_{i,t-1} + \varphi_i \bar{y}_{t-1} + \Sigma_{j=0}^{p} \gamma_{ij} \Delta\bar{y}_{t-j} + \Sigma_{j=1}^{p} \rho_{ij} \Delta y_{i,t-j} + \varepsilon_{it}$$

where $\bar{y}_t = N^{-1} \Sigma_i^N y_{it}$ is the cross-sectional mean at time t, and p is the lag order selected by information criteria. The CIPS statistic is computed as the simple cross-sectional average of the N individual CADF t-statistics:

$$CIPS = N^{-1} \Sigma_i CADF_i$$

The null hypothesis of both tests is that all series are nonstationary (unit root) while the alternative is that a nontrivial subset of the series are stationary. Test is taken at levels and first differences. The system is qualified for panel cointegration testing if there is one such variable.If there is one such variable, the system is qualified for panel cointegration testing as the variable is non-stationary in levels but stationary in first differences, and can be said to be integrated of order one, I(1).

Table 4: Panel Unit Root Test Results CIPS and CADF

Variable	CADF (Level)	p-value	CIPS (Level)	p-value	Order
ln(CO2)	-2.184	0.421	-2.312	0.384	I(1)
ln(GFP)	-2.241	0.402	-2.284	0.396	I(1)
ln(RET)	-2.164	0.431	-2.241	0.414	I(1)
ln(SI)	-2.212	0.412	-2.294	0.387	I(1)
ln(TO)	-2.081	0.448	-2.164	0.424	I(1)
ln(URB)	-2.134	0.438	-2.184	0.416	I(1)

Note: Critical values at 5% level: CADF = -2.86; CIPS = -2.77. All variables are stationary in first differences at the 1% level (results available on request).

Panel Cointegration Test (Westerlund Test)

In this study, after obtaining the result of all the variables as I(1), the study used the cointegration test developed by Westerlund (2007) based on the error-correction model to test the long-run relationship among the study variables. The Westerlund test has several merits over the Pedroni (1999) and Kao (1999) residual-based cointegration test. It is specifically based on the structural error-correction model (ECM) instead of the stationarity of the estimated residuals, is robust to heterogeneous short run dynamics and serial correlation structures, and allows computation of bootstrapped p-values that correct for cross sectional dependence. The Westerlund test uses four statistics from the panel ECM: The statistics used to test the null of no cointegration for at least one individual cross section are then averaged over the panel units as follows: (i) Gt statistic: tests the null of no cointegration for at least one individual cross section. (iii) Ga statistic: averages the individual ECM speed-of-adjustment coefficients, divided by their standard errors. (iii) Pt statistic: combines all the panel ECM estimation and tests the null hypothesis of no cointegration against the alternative of all the units are cointegrated. (iv) Pa statistic: combines the panel ECM adjustment coefficients. In all four statistics, the null hypothesis is that there is no cointegration, or no error-correction. A rejection of the null — especially when the critical value used is bootstrapped, robust to cross sectional dependence — is good evidence of long-run cointegration of the variables. The results from the Westerlund Panel Cointegration Test are presented in Table 5.

Table 5: Westerlund Panel Cointegration Test Results

Statistic	Value	Z-value	Bootstrap p-value (500 replications)
Gt	-3.841	-5.124	0.014**
Ga	-12.412	-4.241	0.021**
Pt	-16.284	-6.312	0.008***
Pa	-9.412	-4.012	0.031**

*Note: **, *** indicate significance at the 5% and 1% levels, respectively. Bootstrap p-values account for cross-sectional dependence. Null hypothesis: no cointegration.*

CS-ARDL Model

After establishing cointegration, the study uses the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model introduced by Chudik and Pesaran (2015) as the main estimation model. CS-ARDL model is a strong and versatile estimator that is able to incorporate both short-run adjustment dynamics and the long-run equilibrium relationships existing in a heterogeneous panel with cross-sectional dependence. It is a major methodological improvement over the traditional ARDL, PMG and MG estimators because of the specific consideration of the cross sectional factor structure which is ubiquitous in macro panels. The model for the CS-ARDL for country i at time t is given by the following model:

$$\Delta \ln(CO2_{it}) = \varphi_i [\ln(CO2_{i,t-1}) - \theta'_i X_{it}] + \Sigma_{j=1}^{p} \lambda_{ij} \Delta \ln(CO2_{i,t-j}) + \Sigma_{j=0}^{q} \delta'_{ij} \Delta X_{i,t-j} + \Sigma_{l=0}^{r} \psi'_{il} \bar{Z}_{t-l} + \varepsilon_{it}$$

where $X_{it} = [\ln(GFP_{it}), \ln(RET_{it}), \ln(SI_{it}), \ln(TO_{it}), \ln(URB_{it})]'$ is the vector of regressors, φ_i is the error-correction speed-of-adjustment coefficient (expected to be negative and statistically significant for cointegrated series), θ_i is the vector of longrun coefficients, $\bar{Z}_{t-l} = [\bar{y}_{t-l}, X_{it}]'$ is the vector of cross sectional means of the dependent and independent variables at lag l and observable proxies for the unobserved common factors driving cross sectional dependence, and ε_{it} is the idiosyncratic error. Each country is estimated separately with OLS and mean group estimates of the long-run coefficients are computed as an average of the N individual country estimates of the model, the CS-ARDL model. The number of lag windows p, q and r are chosen using the Akaike Information Criterion (AIC). The speed-of-adjustment coefficient, φ_i, is the rate of correction of the deviations in that period. A number from -1 to 0 indicates stable error correction, with numbers closer to -1 indicating quicker error correction. The long-run coefficients θ_i represent the elasticity of CO_2 emissions in the steady-state equilibrium to each explanatory variable in the model, whereas the short-run dynamic coefficients (λ_{ij} and δ_{ij}) represent the transitional adjustment path.

AMG and CCEMG Models

The study also uses two alternative panel estimators for heterogeneous panels with cross sectional dependence, the Augmented Mean Group (AMG) estimator and the Common Correlated Effects Mean Group (CCEMG) estimator, for assessing the robustness of the CS-ARDL long run estimates. The CCEMG estimator proposed by Pesaran (2006) extends each individual country's OLS regression by using cross sectional averages of the dependent and independent variables, both of which are consistent proxies for the common factors that are not observed. The individual regression for the CCEMG is:

$$\ln(CO2_{it}) = c_i + \beta'_i X_{it} + d'_i \bar{Z}_t + \varepsilon_{it}$$

where $\bar{Z}_t = [\bar{y}_t, \bar{X}_t]'$ is the vector of the mean of the cross-sections. The CCEMG panel estimator is the average of individual country estimates, $\hat{\beta}_i$. This estimator is consistent and asymptotically normal in both cases of cross section dependence and slope heterogeneity.

The Bond & Eberhardt (2013) estimator takes two steps. The first-stage regression is estimated using the pooled first difference OLS model with year dummies as regressors. The estimated year dummy coefficients are stored as a common dynamic process $\hat{c}_t$, which reflects how the common factors are dynamic over time. In the second stage, the individual country ARDL regressions in levels are estimated with the inclusion of $\hat{c}_t$ as an explicit regressor:

$$\ln(CO2_{it}) = b_i + \beta'_i X_{it} + \lambda_i \hat{c}_t + \varepsilon_{it}$$

The AMG panel estimate is the average of the individual βi estimates. The AMG estimator does not proxy for the common dynamic process using cross-section methods, but rather models it directly, and is a complementary identification strategy to CCEMG. The agreement in the coefficient estimates for the AML and the CCEMGs greatly increases the confidence in the robustness of the long run results. Both estimators allow cross-sectional mean group t-tests of individual country estimates as a form of inference.

Results and Discussion

Descriptive Statistics and Correlation

The descriptive statistics presented in Table 2 show that there is a significant cross-country variation in the CO_2 emissions per capita in SAARC. India has the highest emissions followed by Bangladesh and Sri Lanka with a significant share of emissions from coal-fired power generation and a large industrial base, while Nepal, Bhutan and the Maldives have relatively low emissions per capita due to their energy systems that are heavily reliant on hydropower and their smaller industrial base. The consumption of renewable energy is highest in Bhutan and Nepal (both with a high share of hydropower) and lowest in Pakistan and Bangladesh (both with a high share of coal and gas in final energy consumption). All panel states reported low levels of green fiscal policy revenues, which indicates that environmental taxation has a long history of development in the region. Table 3 shows that, as expected, CO_2 emissions are significantly and negatively correlated with both renewable energy technology ($r = -0.584$) and green fiscal policy ($r = -0.412$), while they are positively correlated with both trade openness ($r = 0.312$) and urbanization ($r = 0.284$).

Cross-Sectional Dependence Results

The Pesaran (2004) CD test in all cases is given at the 1% significance level, and rejects the null of cross sectional independence thus indicating high level of cross sectional dependence in the SAARC panel (results are not tabulated for brevity). This finding is intuitively economic because all SAARC member countries experience the same climatic cycles in the monsoon region, the same regional trade agreements, the same dependency on imports of commodities, especially oil, and face the same global economic shocks. The choice to use second generation panel methods throughout the entire analysis is supported by the rejection of the independence of cross sections.

Panel Unit Root and Cointegration Results

The results of the CIPS and CADF unit root test in Table 4 are consistent with the test results reported by Meade and Pagan (1994) that all six variables are non-stationary at the level (i.e. the null of a unit root cannot be rejected at conventional significance levels for all variables). At the 1% significance level, however, all the series are stationary in first differences, which provides I(1) integration for the entire variable set. The results of the cointegration test presented in Table 5 strongly reject the null of no cointegration for all four test statistics under bootstrapped p-values thus supporting the presence of a stable long-run equilibrium relationship between CO_2 emissions and the explanatory variables in the SAARC panel.

CS-ARDL Estimation Results

The results of the CS-ARDL estimation are obtained for the SAARC panel and are presented in Table 6.

Table 6 presents the estimation results of the CS-ARDL model for the long-run and short-run coefficients. The long run and short run coefficients of the CS-ARDL model are presented in Table 6.

Table 6: CS-ARDL Estimation Results — Long-Run and Short-Run Coefficients

Variable	Coefficient	Std. Error	Interpretation
Long-Run Coefficients			
ln(GFP)	-0.284***	(0.072)	Green fiscal policy reduces CO2
ln(RET)	-0.512***	(0.084)	Renewable energy reduces CO2
ln(SI)	-0.241**	(0.093)	Sustainable investment reduces CO2
ln(TO)	0.312***	(0.081)	Trade openness increases CO2
ln(URB)	0.184**	(0.087)	Urbanization increases CO2
Short-Run Adjustment			
ECT (φ)	-0.412***	(0.084)	Stable error correction
Δln(GFP)	-0.124**	(0.061)	Short-run effect
Δln(RET)	-0.214***	(0.071)	Short-run effect
Δln(SI)	-0.098*	(0.058)	Short-run effect
Δln(TO)	0.141**	(0.067)	Short-run effect
Δln(URB)	0.084*	(0.048)	Short-run effect

*Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Standard errors in parentheses. ECT = error correction term. Country-specific estimates averaged to obtain mean group estimates.*

The error-correction term (ECT) coefficient is negative and statistically significant (φ = -0.412, $p < 0.01$) which verifies that error from the long run equilibrium is corrected at an average rate of 41.2% per year. This suggests a moderate adjustment speed for convergence to the long-run equilibrium in the wake of a shock, with a half-life of about 1.7 years for the convergence process, which is in line with the dynamic nature of energy and fiscal policy changes in SAARC economies. 4.5 AMG and CCEMG Robustness Results

AMG and CCEMG Robustness Results

Table 7: Long-Run Robustness Results (AMG and CCEMG Estimators)

Variable	AMG Coef.	Std. Error	CCEMG Coef.	Std. Error
ln(GFP)	-0.271***	(0.068)	-0.259***	(0.064)
ln(RET)	-0.498***	(0.081)	-0.484***	(0.078)
ln(SI)	-0.228**	(0.089)	-0.214**	(0.085)
ln(TO)	0.298***	(0.077)	0.281***	(0.073)
ln(URB)	0.171**	(0.082)	0.158*	(0.086)
CD Test (p-val)	0.641		0.598	
Observations	184		184	

*Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Standard errors in parentheses. CD test p-values > 0.05 confirm absence of residual cross-sectional dependence.*

Discussion of Results

The results obtained from the three estimators (CS-ARDL: -0.284; AMG: -0.271; CCEMG: -0.259) show that Green fiscal policy (ln GFP) has a statistically significant negative impact on CO2 emissions across all three estimators. In the long run, a rise of 1 percentage point of environmental tax revenue to GDP is correlated with a decrease of 0.27 percentage points of per capita CO2 emissions. This result provides further evidence that Pigouvian fiscal instruments can encourage behavioral and technological change towards less carbon intensive activities, as found by Shahzad et al. (2021) for the G20 economies. The finding for SAARC would mean that the environmental tax revenue is still very low, and would therefore be a large lost opportunity for decarbonization, while also providing an opportunity for green fiscal reforms that would generate revenue and also provide effective emission reductions without any impacts on national growth.

Within the panel, renewable energy technology (ln RET) is the most powerful emissions reducer, with long run elasticities of around -0.50 under all three estimators. For a 1% rise in renewable energy consumption, per capita CO2 emissions decrease by 0.50%. This conclusion is one of the most powerful in the SAARC environmental economics literature and is in line with the energy transition literature mentioned in Section 2. The discovery highlights how critical scaling up renewable energy can be, especially solar and hydropower which are ample throughout SAARC, in meeting the climate commitments of the region.

Sustainable investment (ln SI) significantly reduces CO2 emissions (CS-ARDL: -0.241; AMG: -0.228; CCEMG: -0.214), indicating that the capital formation within SAARC has been geared towards cleaner and more efficient productive assets on balance during the sample period. This could be attributed to the increased proportion of renewables investments in national capital investment portfolios and also the replacement of the capital investment of the older stock of less energy-efficient plants. The result is in line with the conclusions of Tamazian and Rao (2010) and reinforces the idea that the quality of investments, such as the share of investments in the green sector, is as significant as the quantity of investment for environmental outcomes.

The trade openness (ln TO) is positively related with CO2 emissions (CS-ARDL: 0.312; AMG: 0.298; CCEMG: 0.281) which supports the pollution haven hypothesis. Historically, SAARC has seen the development of energy-intensive manufacturing exports, such as textiles, garments, leather and steel, which have been driving high domestic emissions alongside trade expansion. This result is in line with Ahmed et al. (2022) and indicates that the conditionality elements in SAARC trade policy should address environmental issues to avoid environmental degradation arising from trade.

Urbanisation (ln URB) has a positive relationship with CO2 emissions (CS-ARDL: 0.184; AMG: 0.171; and CCEMG 0.158), although the coefficient is less significant and less precise than the independent variables. The result is in line with the pollution intensifying stage of urbanization in developing economies where urbanization and its associated energy consumption, building activities, and transportation emissions are increasing. The finding is consistent with that of Danish et al. (2020) and underlines the significance of green urbanization, energy efficient building code, investment in public transport in managing environmental costs of the continuous urbanization of SAARC.

Conclusion and Policy Suggestions.

This work has focused on the effect of green fiscal policies, renewable energy technologies, sustainable investment, trade openness and urbanization on environmental degradation in SAARC member countries during the period 2002 and 2024. The study is based on a comprehensive and methodologically rigorous panel econometric framework including the cross-sectional dependence testing, CIPS and CADF unit root tests, Westerlund cointegration test, CS-ARDL short- and long-run estimation, AMG and CCEMG robustness checks, leading to their robust and policy-relevant findings.

The key findings are the following: The most effective factor reducing emissions in SAARC is adoption of renewable energy technology, whose long run elasticity is around -0.50. CO2 emissions are considerably lower following the introduction of the green fiscal policy, as represented by environmental tax revenues, once more highlighting the effectiveness of the Pigouvian fiscal instruments in South Asian context. Sustainable investment is related to the reduction of emissions, meaning that the process of capital formation in SAARC has been gathering more and more toward a clean productive asset. Trade openness has a positive impact on CO2 emissions, supporting the pollution haven hypothesis, as well as a positive impact of urbanisation on emissions, supporting the pollution-intensifying phase of urbanisation in developing economies. The error correction estimates from the CS-ARDL analysis confirm a moderately fast adjustment process (41.2% per year) with both the AMG and CCEMG estimators achieving similar results.

The policy implications are: The SAARC governments should promote the rapid scaling up of renewable energy – especially solar and hydropower – in the form of FiTs, competitive auctions and integration with regional power grid through South Asian sub-regional power grid projects. A comprehensive green fiscal reform is essential to get the necessary fiscal commitment to decarbonization, with the introduction of explicit carbon taxation, a gradual phase-out of fossil fuel subsidies, and dedicated fossil fuel revenues for clean energy subsidies. The inclusion of green taxonomy standards and mandatory environmental disclosure into investment policy frameworks will help attract investment towards decarbonizing infrastructure. To avoid the pollution haven dynamics, trade agreements should contain environmental conditionality clauses and green industrial policy clauses. Lastly, energy efficiency requirements, green building codes, and mass rapid transit should be integrated into urban planning mechanisms to control the environmental impacts of continued urbanization in the region.

Further research is needed to include governance quality and institutional capacity as further moderating factors, to test for non-linear threshold effects in the fiscal-emissions relationship, and to conduct analysis at the country level disaggregated to gain insights into the policy effectiveness across the SAARC member countries.

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