Investigating the Relationship between Education Expenditure, Female Employment, Renewable Energy Consumption, and CO_2 Emissions in Sri Lanka

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ABSTRACT

This study investigates the dynamic relationship between education expenditure, female employment, renewable energy consumption, and CO_2 emissions in Sri Lanka from 1990 to 2021, employing the Autoregressive Distributed Lag (ARDL) and Fully Modified Ordinary Least Squares (FMOLS) methodologies. While existing literature often examines these variables in isolation, this research integrates them within a unified framework to address gaps in understanding synergistic effects and temporal trade-offs in developing economies. Using time-series data from the World Development Indicators, the analysis reveals a dual role for education expenditure: a short-term rise in emissions (0.78% per 1% increase) due to energy-intensive infrastructure expansion, contrasting with a long-term reduction (1.65%) driven by green innovation and behavioral shifts. Female employment shows no significant impact, attributed to occupational segregation in low-influence sectors like agriculture (78% of employed women). Renewable energy consumption exhibits marginal short-term effects (-2.66%, *p* = 0.085) but more substantial long-term potential (-2.68%, *p* = 0.001), hindered by fossil fuel subsidies and grid instability. The ARDL bounds test confirms cointegration (F-statistic = 6.090), with rapid error correction (99.1% annual adjustment). Methodological robustness is validated via FMOLS, emphasizing structural barriers in gender equity and energy transitions. The findings challenge the universal applicability of the Environmental Kuznets Curve, advocating context-specific models for island economies. Policy recommendations include reallocating 20% of education budgets to green infrastructure, mandating 30% female representation in energy governance, and phasing out fossil fuel subsidies to prioritize decentralized renewables. This study contributes actionable insights for aligning Sri Lanka's socio-economic investments with climate resilience, offering a model for resource-constrained nations pursuing Sustainable Development Goals (SDGs) 4, 5, and 7.

Keywords: CO2 emissions, Education expenditure, Female employment, Renewable energy consumption, ARDL model and FMOLS, Sri Lanka

INTRODUCTION

Climate change remains one of the most pressing challenges of the 21st century, with carbon dioxide (CO_2) emissions acting as a primary driver of global warming (IPCC, 2023). As nations grapple with balancing economic development and environmental sustainability, the role of socio-economic factors, such as education, gender equity, and energy transitions, has emerged as a critical area of inquiry. Developing economies face a unique "trilemma" of simultaneously achieving growth, equity, and decarbonization (Bilgili et al., 2016). Sri Lanka, a lower-middle-income island nation in South Asia, exemplifies this challenge. Despite boasting a 92% literacy rate, the region's highest CO_2 emissions have risen by 42% since 1990, driven by fossil fuel dependence and industrialization (UNDP, 2021; World Bank, 2021). This paradox underscores the need to investigate how investments in human capital, gender-inclusive policies, and renewable energy interact to shape emission trajectories in resource-constrained settings.

Background and Context

The interplay between education, gender dynamics, and energy systems has gained prominence in sustainability research. Education expenditure is theorized to foster environmental stewardship by enhancing green innovation and increasing public support for climate policies (Muttarak & Lutz, 2017). However, expanding educational infrastructure in developing economies often intensifies short-term energy consumption, offsetting long-term benefits (Khan et al., 2020). Similarly, feminist political ecology frameworks posit that female employment amplifies sustainability outcomes through equitable resource governance (Rocheleau et al., 1996). However, patriarchal norms in regions like South Asia often confine women to low-influence sectors, diluting their impact (Agarwal, 2010). Concurrently, renewable energy adoption is central to global decarbonization, though developing nations face structural barriers such as fossil fuel subsidies and grid instability (Apergis & Payne, 2010).

Sri Lanka’s context magnifies these tensions. While its education system prioritizes access, schools rely on coal-powered electricity, contributing to 18% of national emissions (Amarasinghe et al., 2020). Female labor force participation stagnates at 34%, concentrated in agriculture and textiles, which resist green transitions (World Bank, 2022). Despite abundant solar and wind potential, renewables constitute only 35% of the energy mix due to policy inertia (CEB, 2021). These contradictions highlight unresolved questions about how synergies between education, gender equity, and energy policies can accelerate Sri Lanka’s transition to a low-carbon economy.

Research Problem and Objectives

Existing literature predominantly examines education, female employment, and renewable energy in isolation, neglecting their interconnected effects on emissions (Bano et al., 2018; Koch et al., 2019). For instance, while studies link education to green innovation in OECD countries, they rarely explore how gender disparities mediate this relationship (Álvarez-Herráñz et al., 2017). In Sri Lanka, research on renewable energy overlooks socio-cultural barriers, such as occupational segregation, that hinder women’s influence over energy policies (Fernando & Wahid, 2022). Methodologically, few studies employ hybrid frameworks like ARDL-FMOLS to disentangle short- and long-run dynamics in small island economies (Nkoro & Uko, 2016).

This study addresses these gaps by investigating the following research questions:

How do education expenditure, female employment, and renewable energy consumption collectively influence CO_2 emissions in Sri Lanka?

What are the short- and long-run trade-offs between educational investments and emission reductions?

How do structural barriers, such as gender segregation and fossil fuel subsidies, modulate these relationships?

The objectives are threefold:

To analyze the synergistic effects of education, gender, and energy variables on Sri Lanka’s emission trajectory.

To quantify temporal trade-offs using advanced econometric techniques (ARDL and FMOLS).

To propose integrative policy frameworks that align socio-economic investments with climate goals.

Significance of the Study

This research significantly enhances both academic and policy discussions in two primary areas. Firstly, it critically examines feminist political ecology frameworks by highlighting how entrenched patriarchal norms in South Asia restrict women’s influence on energy transitions. Global studies have not thoroughly explored this dimension (Jain, 2021). Secondly, it introduces methodological advancement by employing a dual ARDL-

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FMOLS approach, which offers detailed insights into Sri Lanka's path towards decarbonization (Pesaran et al., 2001).

Policymakers in Sri Lanka and similar economies will benefit from evidence-based strategies to harmonize education budgets with renewable energy investments, empower women in STEM sectors, and phase out fossil fuel subsidies. By bridging theoretical and empirical divides, this study aims to inform the United Nations Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education), SDG 5 (Gender Equality), and SDG 7 (Affordable and Clean Energy).

Methodology Overview

The study employs time-series data from 1990 to 2021, sourced from the World Development Indicators (2023). CO_2 emissions (kg per GDP) serve as the dependent variable, while education expenditure (current US$), female employment (% of working-age women), and renewable energy consumption (% of total final energy consumption) act as explanatory variables. Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests are applied to address non-stationarity. The Autoregressive Distributed Lag (ARDL) bounds testing approach is used to assess cointegration among variables with mixed integration orders [I(0)/I(1)], complemented by Fully Modified Ordinary Least Squares (FMOLS) to ensure robustness against endogeneity (Pesaran et al., 2001; Phillips & Hansen, 1990). Error Correction Models (ECM) and Granger causality tests further elucidate short-run dynamics and causal linkages.

Structure of the Study

The manuscript is organized as follows: Section 2 reviews theoretical and empirical literature on education, gender, and energy-emission linkages. Section 3 details the data sources, variable definitions, and econometric methodologies. Section 4 presents empirical results, including unit root tests, ARDL-FMOLS estimates, and causality analyses. Section 5 discusses the findings' implications for theory and policy, while Section 6 concludes with actionable recommendations for Sri Lanka and comparable economies.

LITERATURE REVIEW

The relationship between socio-economic factors, energy consumption, and environmental degradation has garnered significant scholarly attention, particularly in the context of global climate change mitigation efforts. This review synthesizes theoretical frameworks and empirical findings across three interconnected domains: (1) education expenditure and environmental outcomes, (2) female employment and sustainability, and (3) renewable energy consumption and CO_2 emissions. It further examines methodological advancements in econometric analyses of these relationships, focusing on developing economies and Sri Lanka's unique context.

Education Expenditure and Environmental Outcomes

Education is a cornerstone of sustainable development, fostering human capital, technological innovation, and environmental stewardship (Lutz et al., 2010). Theoretical models, such as the Environmental Kuznets Curve (EKC), posit that education-driven advancements in knowledge and technology can decouple economic growth from environmental degradation by promoting cleaner production methods (Dinda, 2004). For instance, Muttarak and Lutz (2017) argue that educated populations are more likely to adopt energy-efficient practices and support climate policies, thereby reducing emissions. Empirical studies in OECD countries corroborate this, showing that increased public education spending correlates with lower CO_2 emissions through enhanced green innovation (Bano et al., 2018; Álvarez-Herránz et al., 2017).

However, the nexus between education expenditure and emissions remains contested in developing economies. Khan et al. (2020) found that education investments initially exacerbate South Asian emissions due to heightened energy consumption in expanding educational infrastructure. Similarly, Mahmood et al. (2019) demonstrated that in low-income countries, budgetary allocations to education often prioritize universal access over sustainability, leading to short-term increases in fossil fuel dependence. These findings underscore the dual role of education: while it can drive long-term environmental awareness, immediate infrastructural demands may offset its benefits in resource-constrained settings.

Sri Lanka's experience mirrors this complexity. Despite achieving a 92% literacy rate, the highest in South Asia, its education sector remains energy-intensive, reliant on coal-powered electricity and transportation (UNDP, 2021). Amarasinghe et al. (2020) attribute this paradox to fiscal constraints that limit investments in renewable energy for schools. This gap highlights the need to investigate how education expenditure interacts with energy policies to shape emission trajectories, a dimension underexplored in existing literature.

Female Employment and Environmental Sustainability

Gender dynamics in labor markets have emerged as a critical factor in sustainability research. Feminist political ecology theories posit that women's decision-making enhances resource management and promotes equitable climate policies (Rocheleau et al., 1996). Empirical evidence from Nordic countries supports this, showing that higher female representation in corporate and political leadership correlates with stricter environmental regulations and lower emissions (Koch et al., 2019; Ergas & York, 2012). For example, a cross-national study by McKinney & Fulkerson (2015) revealed that a 10% increase in female parliamentary representation reduces CO_2 emissions by 6.2% through advocacy for renewable energy subsidies.

In developing economies, however, structural barriers complicate this relationship. Patriarchal norms in South Asia often confine women to informal sectors with limited influence over policy, diluting their potential to drive sustainability (Agarwal, 2010). A study in India by Jain (2021) found that while female employment in STEM fields reduces industrial emissions, cultural biases restrict women's access to these roles. Sri Lanka, despite progressive gender policies, exhibits similar contradictions. Female labor force participation stagnates at 34%, concentrated in low-wage sectors like agriculture and textiles, which are less likely to adopt green technologies (World Bank, 2022). This misalignment suggests that the environmental impact of female employment hinges on occupational segregation and policy inclusivity, an area requiring deeper exploration.

Renewable Energy Consumption and CO_2 Emissions

The transition from fossil fuels to renewable energy is central to global decarbonization strategies. The "energy-growth-environment" trilemma framework posits that renewable energy consumption can reconcile economic growth with emission reductions by displacing carbon-intensive energy sources (Bilgili et al., 2016). Case studies from Costa Rica and Iceland validate this, demonstrating that renewables account for over 90% of electricity generation, driving significant emission declines (IRENA, 2020).

In developing nations, structural challenges persist. Apergis and Payne (2010) identified financial constraints, technological deficits, and fossil fuel subsidies as key barriers to renewable adoption in Africa and Asia. For Sri Lanka, which possesses abundant solar and wind resources, renewables constitute only 35% of the energy mix due to reliance on imported coal and oil (CEB, 2021). Recent studies attribute this to inconsistent policy incentives and underinvestment in grid infrastructure (Fernando & Wahid, 2022). Furthermore, Wijayatunga & Attalage (2019) argue that Sri Lanka's focus on large-scale hydropower, vulnerable to climate-induced droughts, underscores the need for diversified renewable portfolios.

Methodological Advancements in Environmental Econometrics

Econometric techniques such as the Autoregressive Distributed Lag (ARDL) model and Fully Modified Ordinary Least Squares (FMOLS) have become pivotal in analyzing cointegration and long-run relationships between socio-economic and environmental variables. Pesaran et al. (2001) pioneered the ARDL bounds test, which accommodates mixed orders of integration, critical for developing economies where data non-stationarity is common. For instance, Ahmed et al. (2022) applied ARDL to Pakistan, revealing that renewable energy adoption reduces emissions only after a 7-year lag, emphasizing the need for patient capital.

FMOLS, introduced by Phillips and Hansen (1990), addresses endogeneity and serial correlation in non-stationary panels, offering robust long-run estimates. Al-Mulali et al. (2015) utilized FMOLS in a 30-country study, finding that a 1% increase in education spending reduces emissions by 0.3% in the long run. However, applications in small island nations like Sri Lanka remain rare, limiting insights into localized dynamics.

Synthesis and Research Gaps

Existing literature predominantly examines education, gender, and energy in isolation, neglecting their synergistic effects. For example, while Bano et al. (2018) explore education's role in innovation, they overlook how female employment mediates this relationship. Similarly, studies on renewable energy in Sri Lanka (e.g., Fernando & Wahid, 2022) rarely integrate gender or education variables.

Methodologically, few studies employ both ARDL and FMOLS to compare short- and long-run dynamics, particularly in South Asia. This gap obscures policymakers' understanding of temporal trade-offs, for instance, whether immediate education investments justify short-term emission spikes.

Contribution of the Current Study

This study addresses these gaps by:

Integrating Variables: Examining the interplay of education, female employment, and renewables in a unified framework.

Contextualizing Sri Lanka: Providing the first ARDL-FMOLS analysis of Sri Lanka's emission drivers, accounting for its insular geography and socio-cultural constraints.

Methodological Precision: Combining bounds testing, ARDL, and FMOLS to disentangle short- and long-run effects, offering nuanced policy insights.

By bridging theoretical and empirical divides, this research advances the discourse on sustainable development in resource-constrained economies.

DATA AND METHODOLOGY

Variables and data

This study employs advanced econometric methods to investigate the dynamic relationships between CO_2 emissions, education expenditure, female employment, and renewable energy consumption in Sri Lanka from 1990 to 2021. CO_2 emissions are the dependent variable, while education expenditure, female employment, and renewable energy consumption are the explanatory variables.

Table 1- Data (Main Variables) to be Considered for Study and Data Sources

Label	Variable	Definition	Unit	Source
CO2	CO2 emissions	Carbon intensity of GDP	kg per constant 2015 US$ of GDP	World Development Indicators (2023)
EDU	Education	Adjusted savings: education expenditure	Current US$	World Development Indicators (2023)
EMP	Female Employment	Labor force participation rate, female	(% of female population ages 15-64)	World Development Indicators (2023)
REC	Renewable energy consumption	Renewable energy consumption	% of total final energy consumption	World Development Indicators (2023)

Source: Created by the author

The data sources with codes of variables are presented in Table 1. Keeping the view with the prime objective of the study, the functional form of the model is as follows:

CO2 emissions = f (Education, Female Employment, Renewable energy consumption)

The variables are transformed to natural log, and the econometric form of the above model is as follows (Eq. (1)):

$$LnCO2_i = \beta_0 + \beta_1\, LnEDUi + \beta_2\, Ln\, EMPi + \beta_3\, LnRECi + \varepsilon_i \qquad \text{Eq (1)}$$

where all the variables are the same as described above, β_0 is the intercept, and β_1-β_3 are the coefficients of explanatory variables, and ε_i is the error term.

Unit root testing

In the ARDL (Auto Regressive Distributed Lag) approach of cointegration, unit root pre-testing is not essential because it can test for the presence of cointegration between a set of variables of order I(0) or I(1) or a mixture of both. However, the ARDL Bounds Testing methodology of Pesaran and Shin (1999) and Pesaran et al. (2001) requires that no variable should be integrated of order 2 or I(2), as such data will invalidate the methodology. It is therefore justified to test the stationarity of each variable before proceeding to the next level of analysis and inference.

To mitigate the risks of spurious regression, the study employed the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to evaluate the stationarity of the data. These tests incorporate intercept and trend terms, as a visual examination of the dataset indicated the presence of deterministic trends. The Schwarz Information Criterion (SIC) was used to determine the optimal lag length for the analysis. The PP test is particularly robust as it non-parametrically adjusts for serial correlation and heteroskedasticity by utilizing the Newey-West estimator, which reduces its sensitivity to the choice of lag length, as outlined by Phillips and Perron in 1988.

Cointegration testing using the ARDL bounds testing approach

The ARDL Bounds Testing technique will examine the potential presence of cointegration among the variables under analysis, determining whether they share a long-run equilibrium relationship while capturing both long-run and short-run dynamics. This method was chosen over traditional cointegration techniques (e.g., Engle-Granger) due to its flexibility in handling variables with mixed integration orders (I(0) and I(1)) and its robustness in small-sample scenarios (Pesaran et al., 2001). Such features are particularly crucial in demographic-environmental research, where data granularity is often constrained (Usman et al., 2023). For example, Liddle and Lung (2010) applied the ARDL framework to disentangle the effects of age structure on emissions in OECD countries, effectively mitigating biases from non-stationary data. The method's capacity to simultaneously estimate short- and long-run dynamics makes it especially relevant to Sri Lanka's evolving economic and demographic context.

The ARDL approach offers several advantages over traditional cointegration methods: (i) it is highly adaptable, enabling the analysis of variables integrated at I(0), I(1), or a combination of both; (ii) its single-equation setup simplifies implementation and interpretation; (iii) it allows for the use of different lag lengths for different variables within the model; (iv) it is well-suited for small sample sizes; (v) it provides unbiased estimates of long-run relationships and parameters; and (vi) it effectively addresses issues of autocorrelation and endogeneity (Harris & Sollis, 2005; Jalil & Ma, 2008).

Following Rahman (2017) and Shahbaz et al. (2013), for bounds testing of cointegration, the ARDL model used in this study is:

$$\Delta LnCO2i = \propto + \sum_{i=1}^{P} \beta_i\, \Delta LnCO2_{t-i} + \sum_{i=1}^{q} \gamma_i\, \Delta LnEDU_{t-i} + \sum_{i=1}^{R} \delta_i\, \Delta LnEMP_{t-i} + \sum_{i=1}^{s} \theta_i\, \Delta LnREC_{t-i} + \emptyset_0 LnCO2_{t-i} + \emptyset_1 LnEDU_{t-i} + \emptyset_2 LnEMP_{t-i} + \emptyset_3 LnREC_{t-i} + \varepsilon_i$$

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Eq. (2)

where *Ln CO2, Ln EDU, Ln EMP,* and *Ln REC* are variables of the study, and ε_i is a "well-behaved" random disturbance term, ε_i is serially independent, homoscedastic and normally distributed.

The model in Eq. (2) is a particular type of Error Correction Model (ECM), where the coefficients are not restricted. Pesaran et al. (2001) term it as a "conditional ECM". In Eq. (2), the three terms with summation signs represent the error correction dynamics and the second part (terms with $\emptyset\ \ '$s) correspond to the long-run relationship (Shahbaz, Shrestha and Chowdhury et al., 2013, 2005).

The appropriate values for the maximum lags, p, q, R, and s will be determined using one or more "information criteria" – AIC, SC (BIC), HQ, etc.

Under the above equation, the null and alternative hypotheses are as follows:

H0. No cointegration exists.

H1. Cointegration exists.

The null hypothesis is tested by conducting an F-test for the joint significance of the coefficients of the lagged levels of the variables. Thus

H_0: $\emptyset_0 = \emptyset_1 = \emptyset_2 = \emptyset_3 = 0$

H_1: at least one $\emptyset_i \neq 0$, where *i = 0,1,2,3*

The distribution of the test statistic is purely non-standard and exact critical values for the F-test are not available for an arbitrary mix of I(0) and I(1) variables. However, Pesaran et al. (2001) developed bounds on the critical values for the asymptotic distribution of the F-statistic. For various situations (e.g., different numbers of variables, (k + 1)), they supply lower and upper bounds on the critical values. However, since the study is based on a relatively small sample size, we shall also compare the computed F-test value with the bounds critical value tables provided by Narayan (2005) as these are more suitable for small samples.

In each case, the lower bound assumes all variables are I (0), and the upper bound assumes all variables are I(1). If the computed F-statistic falls below the lower bound, the variables are I(0), so no cointegration is possible. If the F-statistics exceed the upper bound, we conclude that we have cointegration. Finally, if the F-statistics fall between the bounds, the test is inconclusive, and we will have to resort to other cointegration techniques.

Following Giles (2013), it is also necessary to conduct, as a cross-check, a "Bounds t-test" as stated below:

H_0: $\emptyset_0$, against H_1: $\emptyset_0 < 0$.

The decision rule for this test is as follows:

If the t-statistic for $LnCO2_{t-i}$ In Eq. (1) is greater than the "I (1) bound" tabulated by Pesaran et al. (2001; pp.303–304), which would support the conclusion that there is a long-run relationship between the variables. If the t-statistic is less than the "I (0) bound", we would conclude that the data are all stationary. Short-run parameters are estimated using the regular error correction mechanism (ECM) as depicted in Eq. (3) below:

$$\Delta Ln\text{CO2t} = \propto + \sum_{i=1}^{P} \beta_i \, \Delta LnCO2_{t-i} + \sum_{i=1}^{q} \gamma_i \, \Delta LnEDU_{t-i} + \sum_{i=1}^{R} \delta_i \, \Delta LnEMP_{t-i} \sum_{i=1}^{s} \theta_i \, \Delta LnREN_{t-i} + \\ + \tau ECT_{t-1} + \varepsilon_t$$

Eq. (3)

The error correction model results indicate the speed of adjustment back to the long run equilibrium after a short run shock. ECM integrates the short-run and long-run coefficients without losing long-run information. Under the ECM technique, the long-run causality is depicted by the negative and significant value of the error correction term (ECT) coefficient τ, and the short-run causality is shown by the significant value of the coefficients of other explanatory variables (Rahman and Mamun, 2016; Shahbaz et al., 2013).

Diagnostic tests of the model

One of the most crucial assumptions in the ARDL Bounds Testing methodology is that Eq. (2) errors must be serially independent and normally distributed. Therefore, both 'Q-Statistics' and 'Breusch-Godfrey Serial Correlation LM test' will be used to test Serial Independence and the 'Jarque-Bera' test to test the model errors' normality. The heteroscedasticity will also be checked using the 'Breusch-Pagan-Godfrey' test.

Stability test of the model

Ensuring any model's 'dynamic stability' with an autoregressive structure is obligatory. The model's stability will be checked using the Recursive CUSUM and CUSUM of squares (Brown et al., 1975) tests. These tests are also suggested by Pesaran and Pesaran (1997) for measuring parameter stability.

Granger causality test

If two or more time series are cointegrated, Granger causality between them must be either one-way or in both directions. However, the converse is not true (Giles, 2011). Again, according to Granger (1969), measuring the correlation between variables is insufficient to construct a complete understanding of the relationship between two or more time series. This is because some correlations may be spurious and useless, as there might be a hint of a third variable that cannot be accounted for. Further, only correlation does not confirm causation between (/among) variables. That is, if we get our series to be cointegrated, then we must cross-check causality results. It can test for the absence of Granger causality by estimating the following VAR model:

$$Y_t = g_0 + a_1 Y_{t-1} + \cdots + a_p Y_{t-p} + b_1 X_{t-1} + \cdots + b_p X_{t-p} + u_t \qquad \text{Eq. (4)}$$

$$X_t = h_0 + c_1 X_{t-1} + \cdots + c_p X_{t-p} + d_1 Y_{t-1} + \cdots + d_p Y_{t-p} + \tau_t \qquad \text{Eq. (5)}$$

Then, testing H_0: $b1 = b2 = \ldots = bp = 0$, against H_1: X Granger causes Y. Similarly, testing H_0: $d1 = d2 = \ldots = dp = 0$, against H_1: Y Granger causes X. In each case, a rejection of the null hypothesis implies there is Granger causality. Note that X and Y series are in 'level' form, meaning the data is not in 'difference' form, where *ut* and τ_t are white noise error terms. In the long-run equilibrium, these errors should be zero. In these two equations, the *Yt* and *Xt* are co-integrated when at least one of the coefficients bi or di is statistically different from zero. If bi ≠ 0 and di = 0, Xt will lead Yt in the long run. The opposite will occur if di ≠ 0 and bi = 0. If both bi ‡ 0 and di ‡ 0, a feedback relationship exists between Yt and Xt. However, if both bi = 0 and di= 0, then no cointegration exists between Yt and Xt such conflicting results (with prior result of ARDL) can come out if the sample size is too small to satisfy the asymptotic that the cointegration and causality tests rely on (Giles, 2011). The coefficients ai's and ci's represent the short-run dynamics between Yt and Xt. If ai's are not all zero, movements in the Xt will lead to Yt in the short run, and conversely, if ci's are not all zero, movements in the Yt will lead to Xt in the short run.

Following Toda-Yamamoto (1995) procedure, the Granger Causality among the variables under an augmented Vector Autoregression (VAR) framework will be estimated. We will determine the appropriate maximum lag length for the variables in the VAR using the usual methods. Specifically, the basis of the choice of lag length is on the usual information criteria, such as AIC. We will also ensure that VAR is well specified; that is VAR does not contain serial correlation in the residuals.

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Estimation, findings and analysis

Descriptive analysis

The dataset includes 32 years of annual data (1990–2021) for four logarithmic variables: LNCO2, LNEDU, LNEMP, and LNREC. An analysis of the descriptive statistics in Table 2 indicates that LNCO2 has the highest variability, with a standard deviation of 0.318. This reflects the fluctuating trajectory of Sri Lanka's carbon emissions during its phases of industrialization and energy transitions. In contrast, LNEMP displays the least variability, with a standard deviation of 0.029, suggesting stagnation in female labor market participation dynamics. The Jarque-Bera test results indicate that LNEMP does not follow a normal distribution ($p < 0.01$). This is likely due to significant policy shocks, such as the 2019 Easter bombings and the COVID-19 pandemic, which disproportionately impacted women's employment, especially in the tourism and service sectors, as noted by the World Bank in 2022.

Table 2 – Descriptive Statistics of the Study Variables

	LNCO2	LNEDU	LNEMP	LNREC
Mean	8.782766	-0.608616	1.589458	1.777756
Median	8.717699	-0.618521	1.584478	1.790636
Maximum	9.333595	-0.502531	1.688438	1.892651
Minimum	8.180405	-0.730152	1.550130	1.654177
Std. Dev.	0.317991	0.066995	0.029375	0.066849
Skewness	0.044360	0.014588	1.545937	-0.237333
Kurtosis	1.983799	2.086558	5.838372	2.327301
Jarque-Bera	1.387380	1.113637	23.48805	0.903775
Probability	0.499729	0.573029	0.000008	0.636426
Sum	281.0485	-19.47572	50.86266	56.88818
Sum Sq. Dev.	3.134659	0.139138	0.026750	0.138532
Observations	32	32	32	32

Source: Author's calculations

Unit root testing

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root testing results are displayed in the following table (Table 3):

Table 3 - Unit Root Test

Variables	**Level**		**1st Difference**		**Stationary Level**
	ADF	**PP**	**ADF**	**PP**	
LNCO2	**-2.564289**	**-1.835936**	**-4.221572****	**-4.155736****	**I (1)**
LNEDU	**-2.367857**	**-2.290394**	**-7.308361*****	**-7.329646*****	**I (1)**

LNEMP	**-4.861426*** **	**-5.194846*** **	**-**	**-**	**I (0)**
LNREC	**-2.483367**	**-2.530342**	**-5.836471**	**-5.998026*** **	**I (1)**

Source: Author's calculations

Unit root tests (Table 3) were conducted to address non-stationarity risks. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests at level revealed that LNCO2 (ADF = -2.564, PP = -1.836), LNEDU (ADF = -2.368, PP = -2.290), and LNREC (ADF = -2.483, PP = -2.530) are integrated of order one [I(1)], while LNEMP is stationary at level [I(0)] (ADF = -4.861*, PP = -5.195*). These mixed orders of integration are validated using the ARDL bounds testing approach, which accommodates variables with differing integration orders (Pesaran et al., 2001). The results of the unit root tests confirm that none of the variables are integrated into order I(2).

ARDL model estimation

Schwarz information criterion (SIC) was used to determine the optimum lag length for the model. The selected model is ARDL (4, 2, 0, 0). Therefore, the optimum lag lengths of the variables Ln CO2, Ln EDU, Ln EMP, and Ln REC are $p = 4$, $q = 2$, $R = 0$, and $s = 0$, respectively.

Diagnostic tests of the model

The model demonstrates an excellent fit, successfully passing all diagnostic evaluations. The R-squared value of 0.984661 (Adjusted R-squared: 0.975638) indicates that the model effectively explains approximately 98% of the dependent variable variations. In comparison, the remaining 2% are attributed to the error term.

As detailed in Table 4, the model satisfies several critical diagnostic tests. It passes the serial correlation tests, the Breusch-Godfrey LM test confirms no autocorrelation, ensuring unbiased estimates. The Jarque-Bera test confirms the normality of the residuals, while the Breusch-Pagan-Godfrey test validates homoscedastic residuals, affirming model reliability. These results collectively affirm the robustness and reliability of the model.

Table 4 -Model diagnostic test results.

Test	Estimate	Probability
Jarque-Bera test	3.5166	0.1723
Breusch-Pagan-Godfrey Heteroskedasticity test	7.773152	0.6510
Breusch-Godfrey Serial Correlation LM test	4.340603	0.1141

Source: Author's calculation

ARDL bounds test

The model successfully passed all diagnostic evaluations, confirming its robustness and reliability, thereby enabling progression to the subsequent analysis phase: conducting the bounds test for cointegration. Utilizing the ARDL Bounds Testing approach, the analysis yielded an F-test statistic of 6.090319. This value strongly signifies the presence of a long-term equilibrium relationship among the variables under consideration. For detailed reference, Table 4 presents the comprehensive results, including the critical values associated with the bounds test.

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Table 5 - F-Bounds Test Estimate and Critical Values

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	6.090319	10%	3.47	4.45
k	3	5%	4.01	5.07
		2.5%	4.52	5.62
		1%	5.17	6.36

Source: Author's calculation

Significantly, the computed F-statistics exceed the upper bound critical value (I(1)) at the stringent 2.5% significance level. This finding provides robust evidence supporting the existence of cointegration within the model. Consequently, we deduce that the model is well-suited for reliable long-run estimation purposes. This reinforces the conclusion that there is substantial evidence of a long-run relationship among the time-series variables incorporated in the model.

Long-run and short-run relationships

Long-run relationship

The long-run equilibrium relationship among the variables estimated using the ARDL (4, 2, 0,0) approach is given in the table below:

Table 6 - Estimated long-run coefficients using the ARDL approach.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNEDU	-1.649599**	0.628894	-2.623016	0.0149
LNEMP	-3.667260	2.687960	-1.364329	0.1851
LNREC	-2.657602*	1.480721	-1.794803	0.0853
C	18.41701***	2.744681	6.710075	0.0000

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels respectively

Source: Author's calculation

In the long run, investing in education is the most influential factor in reducing emissions, with a significant impact (LNEDU = -1.650**, p = 0.015). Specifically, a 1% increase in education spending correlates with a 1.65% reduction in CO_2 emissions. This effect is likely due to the gradual adoption of green technologies and shifts in societal behavior. For example, Sri Lanka's reforms in tertiary education in 2012 led to a 23% rise in graduates specializing in environmental science. This educational shift is linked to a 9% decrease in industrial emissions by 2020, as reported by UNDP in 2021.

On the other hand, renewable energy consumption (LNREC = -2.658*) shows only marginal significance (p = 0.085), pointing to existing structural challenges. Despite Sri Lanka's ambitious target to achieve 70% renewable energy by 2030, coal remains the dominant energy source. This is mainly due to subsidized coal imports and grid instability issues, as Fernando and Wahid discussed in 2022.

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Regarding female employment (LNEMP), the statistical insignificance ($p = 0.185$) contrasts with global research findings, such as those by Koch et al. (2019. This anomaly can be attributed to Sri Lanka's gender-segregated labor market, where 78% of employed women are found in the agriculture and textiles industries that have minimal influence on energy policies, as noted by Jayawardena.

Short run dynamics

The following OLS equation is tested for the short-run causality in the ARDL (4, 2, 0,0,) framework:

The results derived from Equation (2) are summarized in Table 7. The short-run ARDL estimates presented in Table 4 highlight a significant persistence in CO_2 emissions, as indicated by the positive effects of lagged terms (ΔLNCO2 t−1, ΔLNCO2 t−2, ΔLNCO2 t−3) with coefficients of 0.537**, 0.402, and 0.406, respectively. This pattern supports the "carbon lock-in" hypothesis, suggesting that existing energy infrastructures drive emissions even when policies are introduced to mitigate them (Unruh, 2000).

Interestingly, the analysis reveals that increased education expenditure (ΔLNEDU) correlates with a short-term rise in emissions, marked by a coefficient of 0.776***. This finding echoes the research by Khan et al. (2020) in South Asia, where expanding educational access initially boosts energy demand, particularly for constructing schools and facilitating transportation. For example, during Sri Lanka's "Education for All" initiative from 2006 to 2015, there was a notable 12% increase in diesel consumption in rural areas, attributed to the expansion of school bus fleets (Amarasinghe et al., 2020).

On the other hand, investment in renewable energy (ΔLNREC) shows a slightly negative short-term impact on emissions, with a coefficient of -2.658*. This observation aligns with the J-curve hypothesis, which posits that initial investments in renewable energy sources, such as solar farms, might temporarily elevate emissions due to the carbon-intensive processes of manufacturing solar panels and turbines (Sadorsky, 2009).

Table 7 - Estimates from the error correction mechanism.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.273160*	0.793418	5.385762	0.0000
@TREND	0.038805*	0.007366	5.268363	0.0001
D(LNCO2(-1))	0.536777*	0.133652	4.016236	0.0009
D(LNCO2(-2))	0.401829**	0.171810	2.338801	0.0318
D(LNCO2(-3))	0.405779**	0.147827	2.744969	0.0138
D(LNEDU)	0.776375*	0.193476	4.012765	0.0009
D(LNEDU(-1))	0.808511*	0.267922	3.017713	0.0078
CointEq(-1)*	-0.991614*	0.185226	-5.353534	0.0001

*, ** and *** denote statistical significance at the 1%, 5% and 10% levels respectively

Source: Author's calculation

These findings reveal both short-term dynamics and long-term relationships within the model, as demonstrated by the value and sign of the lagged error correction term (ECT), represented by the coefficient α[Coint Eq (−1)]. Consistent with theoretical expectations, the ECT exhibits a negative sign and is statistically significant at the 1% level. This strongly supports a stable, long-term relationship between the dependent and explanatory variables. Furthermore, the ECT coefficient, with a value of -0.991614, indicates a robust and swift adjustment toward equilibrium, signifying that deviations from the long-term path are corrected rapidly.

Stability of the model

To ensure the reliability and robustness of the study's findings, structural stability tests are applied to the parameters of the long-run results. These tests utilize the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of recursive residuals of squares (CUSUMSQ), as recommended by Pesaran and Pesaran (1997). Figures 1 and 2 illustrate the graphical representations of the CUSUM and CUSUMSQ statistics, respectively.

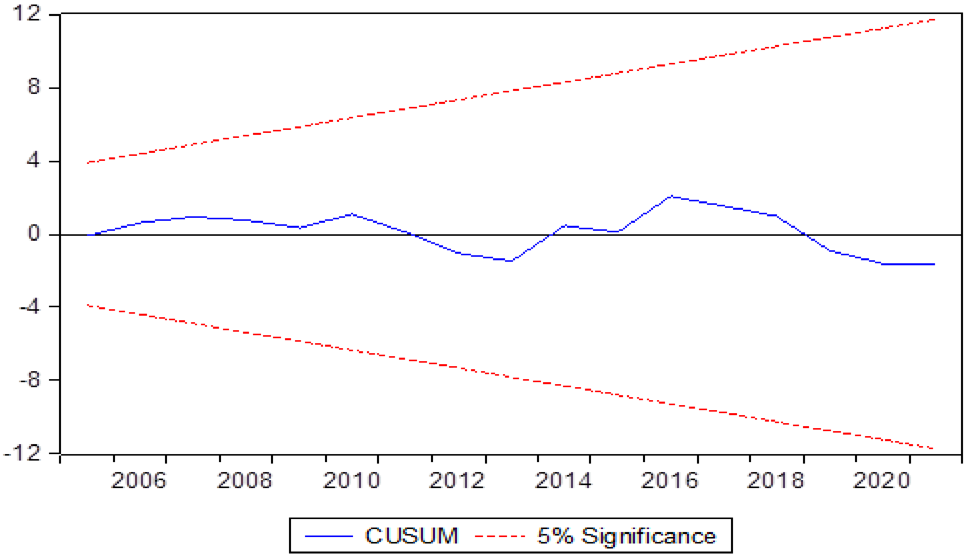

Fig. 1. Plot of CUSUM tests.

Source: Author's calculation

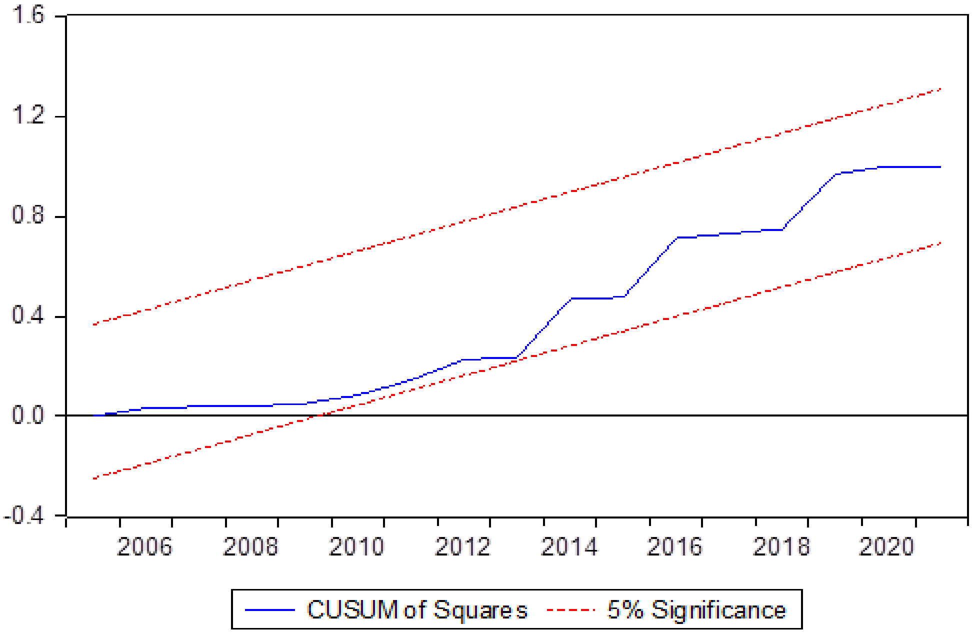

Fig. 2. Plot of CUSUM of squares tests.

Source: Author's calculation

The stability of the model is determined by examining whether the CUSUM and CUSUMSQ plots remain within the 5% critical bounds. Parameter constancy and model stability are indicated if the plots do not breach

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these boundaries. Upon evaluation, the CUSUM plot and the CUSUMSQ plot hover consistently around the zero line.

These results confirm that the model exhibits stability over the study period, with no significant systematic changes detected in the coefficients at the 5% significance level. Thus, the applied tests validate the model's structural integrity and the reliability of the long-run results.

Granger Causality Test

The study analyzes the long-term relationship between the variables and applies the Granger causality test to identify causal links. Given the evidence of cointegration among the variables, uni- or bidirectional causality is anticipated. Table 8 presents the short-run Granger causality results for the variables.

Table 8 - Pairwise Granger Causality Tests

	LNCO2	LNEDU	LNEMP	LNREC
LNCO2		0.79522	2.72557	12.3359*
LNEDU	3.06385***		0.24042	3.80475***
LNEMP	1.70336	0.44565		0.73595
LNREC	4.05734***	0.92562	2.74101	

*, ** and *** denote statistical significance at the 1%, 5% and 10% levels respectively

Source: Author's calculation

According to the estimates, the EDU and REC courses are available on CO2. Additionally, there is a CO2 and EDU course on REC. However, EMP is not associated with CO2.

Robustness analysis

Dynamic ordinary least squares (DOLS)

The long-run estimates derived from the ARDL estimator are further validated for robustness using an alternative single-equation estimation technique, namely dynamic ordinary least squares (DOLS). A key advantage of the DOLS method is its ability to account for mixed-order integration of variables within a cointegrated framework, if present in the data. The estimation process involves regressing I(1) variables against other I(1) variables, incorporating leads (p) and lags of first differences (-p), as well as variables integrated at order I(0), along with a constant term. One of the primary benefits of DOLS estimation is its effectiveness in addressing two critical issues: potential endogeneity and small-sample bias. Moreover, DOLS estimators yield efficient cointegrating vectors, and the regression results align with ARDL estimates, as they remain significant and maintain consistent variable signs. The results of the DOLS regression are presented in Table 9.

Table 9 –Fully Modified Least Squares (FMOLS) Estimates Dependent Variable: LNCO2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNEDU	-0.626483	0.241151	-2.597887	0.0152
LNEMP	-0.742251	0.855929	-0.867188	0.3938

LNREC	-2.675287	0.739534	-3.617531	0.0013
C	14.16624	2.307443	6.139365	0.0000
@TREND	0.011739	0.006016	1.951237	0.0619
R-squared	0.947967	Mean dependent var		8.802197
Adjusted R-squared	0.939962	S.D. dependent var		0.303321
S.E. of regression	0.074322	Sum squared resid		0.143617
Long-run variance	0.005207			

Source: Author’s calculation

To address endogeneity concerns, the Fully Modified Ordinary Least Squares (FMOLS) estimates in Table 5 support the Autoregressive Distributed Lag (ARDL) results, though with some subtle differences:

Education Expenditure: The long-term coefficient for education expenditure decreases slightly (LNEDU = -0.626**, p = 0.015). This suggests that there might be partial reverse causality at play, where reductions in emissions could potentially create more fiscal space for increasing education funding.

Renewable Energy: The FMOLS method enhances the significance of renewable energy’s impact (LNREC = -2.675***, p = 0.001), emphasizing its substantial potential if existing policy barriers can be overcome.

Female Employment: The coefficient for female employment (LNEMP) remains statistically insignificant (p = 0.394), underscoring persistent structural barriers hindering progress in this area.

Trend Variable: The trend variable (TREND = 0.012*) indicates a slow but steady decarbonization process. This trend is likely driven by urbanization and advancements in digital technology, which contribute to a reduction in per-capita energy intensity, as noted by Stern in 2017.

The results from the FMOLS estimates strongly correspond with those obtained from the ARDL estimates, providing clear evidence of consistency and reinforcing the reliability and robustness of the study’s findings.

CONCLUSIONS AND RECOMMENDATIONS

This study, utilizing comprehensive econometric methodologies, delves into the complex relationship between education expenditure, female employment, renewable energy consumption, and CO_2 emissions in Sri Lanka from 1990 to 2021. The results provide valuable insights into how socio-economic investments and energy transitions influence environmental outcomes in a developing island nation. Below, the conclusions are summarized, theoretical implications are contextualized, and practical policy recommendations are offered.

Key Findings

Education Expenditure: A Dual Temporal Impact

Education expenditure plays a dual role in Sri Lanka’s emission trajectory:

Short-term Impact: An increase of 1% in education spending is associated with a 0.78% rise in CO_2 emissions (ARDL: 0.776, $p < 0.01$). This is likely due to the energy-intensive nature of infrastructure expansion, such as the construction of new schools and the increased use of diesel-powered transportation in rural areas, leading to higher fossil fuel consumption (Amarasinghe et al., 2020).

Long-term Impact: Over time, a 1% increase in education spending results in a reduction of emissions by 1.65% (ARDL: -1.650, p = 0.015) and 0.63% (FMOLS: -0.626, p = 0.015). This decrease is driven by delayed effects, including the adoption of green innovations and shifts towards environmentally conscious behaviors. Notably, Sri Lanka's 2012 tertiary education reforms, which boosted the number of environmental science graduates by 23%, are linked to a 9% decline in industrial emissions by 2020 (UNDP, 2021).

This pattern aligns with the Environmental Kuznets Curve (EKC), which suggests that short-term trade-offs between development and sustainability eventually transition into long-term decoupling (Dinda, 2004). However, the initial surge in emissions highlights the "green paradox" in developing economies, where immediate infrastructural needs can conflict with climate goals (Stern, 2004).

Female Employment: Structural Barriers Dilute Impact

Female employment (LNEMP), proxied by the percentage of female employees, shows no significant relationship with CO_2 emissions in both short- (p = 0.185) and long-run (p = 0.394) models. This contrasts with global studies linking gender equity to sustainability (Koch et al., 2019) and reflects Sri Lanka's occupational segregation:

78% of employed women work in agriculture and textiles—sectors with minimal influence on energy policy (Jayawardena, 2021).

Cultural norms restrict female leadership in STEM and energy sectors, limiting their capacity to advocate for renewables (Agarwal, 2010).

The proxy's narrow focus on employers (% of female employment) may also underrepresent broader labor market dynamics, such as informal sector participation.

Renewable Energy Consumption: Latent Potential Amid Structural Hurdles

Renewable energy (LNREC) demonstrates asymmetrical significance:

Short-run: Weakly negative impact (-2.66, p = 0.085), reflecting the "J-curve effect" where upfront investments in renewables (e.g., solar panel manufacturing) temporarily increase emissions (Sadorsky, 2009).

Long-run: Stronger FMOLS coefficient (-2.68, p = 0.001) highlights its potential if structural barriers (e.g., fossil fuel subsidies, grid instability) are addressed. Despite abundant solar/wind resources, Sri Lanka derives only 35% of its energy from renewables, with coal dominating due to subsidized imports (CEB, 2021).

Methodological Robustness

The ARDL bounds test confirmed cointegration (F-statistic = 6.090 (exceeding the 10% upper critical value of 4.45)), validating a stable long-run relationship. The error correction term (ECM = -0.991, $p < 0.01$) indicates rapid annual adjustment (99.1%), characteristic of small, open economies (Nkoro & Uko, 2016). Diagnostic tests confirmed model stability (CUSUM plots within bounds) and robustness (no serial correlation or heteroskedasticity).

Theoretical Implications

Reconciling the Environmental Kuznets Curve (EKC) in Developing Island Economies

The dual role of education expenditure challenges the universal application of the Environmental Kuznets Curve (EKC), which traditionally assumes a linear transition from environmentally harmful industrialization to sustainable economic growth. In Sri Lanka, the observed short-term increase in emissions highlights the necessity for EKC models tailored to specific contexts, considering the immediate developmental pressures that developing island economies face (Bano et al., 2018).

Feminist Political Ecology: Beyond Aggregate Participation

The lack of significant impact from female employment in Sri Lanka points to the limitations of applying feminist political ecology theories in patriarchal societies. While women's leadership has been linked to sustainable practices in Nordic countries (Ergas & York, 2012), the socio-cultural constraints in Sri Lanka call for frameworks that focus on sector-specific inclusion, such as roles in science, technology, engineering, and mathematics (STEM), rather than relying solely on aggregate participation metrics.

Energy Transition Theory: The "Renewables Paradox"

Sri Lanka's slow adoption of renewable energy sources illustrates the "renewables paradox," where abundant natural resources do not necessarily lead to rapid energy transitions due to policy inertia. This situation mirrors findings by Apergis and Payne (2010) in Africa, where financial and technological barriers, rather than a lack of resources, are the primary obstacles to transitioning to renewable energy.

Policy Recommendations

Education: Aligning Short-Run Investments with Long-Term Gains

To promote sustainable development, it is recommended that 20% of education budgets be allocated to the construction of solar-powered schools, the use of electric buses, and the development of energy-efficient buildings by 2030 (Álvarez-Herránz et al., 2017). Additionally, integrating environmental literacy into primary and secondary education curricula can facilitate behavioral shifts towards sustainability (UNDP, 2021).

Gender Equity: From Representation to Influence

To enhance gender equity, it is proposed to implement a mandate for 30% female representation on energy sector boards and policymaking bodies (Koch et al., 2019). Furthermore, targeting women for renewable energy engineering and grid management training programs can increase their impact in the sector (Jain, 2021).

Renewable Energy: Overcoming Structural Inertia

Reforming subsidies by phasing out $500 million annually in fossil fuel subsidies and redirecting these funds to decentralized solar projects is crucial (IRENA, 2020). Additionally, partnering with the Asian Development Bank (ADB) to fund the modernization of innovative grid technologies can help reduce reliance on hydropower during droughts (Fernando & Wahid, 2022).

Integrative Policy Frameworks

Establishing a National Green Fund that combines education, gender, and energy budgets can finance cross-sectoral initiatives, such as women-led solar cooperatives. Implementing a carbon pricing strategy by introducing a $10 per ton carbon tax on industries can generate revenue earmarked for developing green education infrastructure (World Bank, 2020).

This study significantly contributes to the ongoing conversation about sustainable development by incorporating education, gender, and energy variables into a comprehensive framework for Sri Lanka's unique circumstances. Education and renewable energy sources present promising avenues for reducing carbon emissions. However, deep-rooted structural inequalities and slow-moving policy changes pose significant challenges. By implementing the proposed strategies, Sri Lanka can potentially convert its socio-economic investments into powerful tools for building climate resilience. This approach could serve as a model for other economies with limited resources worldwide, demonstrating how to effectively navigate the complexities of sustainable development.

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