Economic Complexity and Its Role in Shaping Renewable Energy Consumption Patterns in Selected South Asian Countries

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Abstract

This research explores the role of economic complexity in driving renewable energy consumption in selected south Asian countries. Using panel data of 4 South Asian countries (Bangladesh, India, Pakistan, and Sri Lanka) from 1990 to 2021, we find a significant long-run relationship among the variables, establishing the interconnected dynamics within the energy sector. We estimate short-run and long-run effects using Pooled Mean Group (PMG) and Common Correlated Effect Pooled Mean Group (CCEPMG). Key findings demonstrate the positive impact of economic complexity on renewable energy consumption, emphasizing its role in transitioning economies toward sustainable practices through technological sophistication. Governments in South Asia should consider implementing targeted incentives for renewable energy infrastructures and research and development for complex economic sector, such as subsidies or tax breaks for foreign and domestic investors. Additionally, fostering trade agreements that prioritize clean energy technologies and reducing dependency on fossil fuels through gradual transition plans are essential steps.

Key Words: Economic Complexity, Renewable Energy, South Asia, PMG and CCEPMG.

JEL Classification: O1, O3 and Q2.

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1. Introduction

The world energy landscape is undergoing a sea change and is driven by the need to transition toward more renewable and sustainable sources of energy. With the ever-increasing impacts of climate change in most parts of the world, the need to keep up the quest for clean, renewable, carbon-neutral energy and have energy security remains the shared priority. According to the 2023 International Energy Agency Electricity Report, renewable energy accounted for 29% of global electricity generation in 2022 with a forecasted increase to 35% by 2025 (IEA, 2023b). Similarly, investment in clean energy has risen by 40% as nations step up their race to abate climate change (IEA, 2023b). The adoption and use of renewable energy are now at the forefront of global efforts to tackle environmental crises caused by degradation and to ensure a sustainable future for the future generation. However, the distribution and consumption of renewable energy is unequal across the globe, with significant variations between developed, developing, and low-and-middle income regions (Li et al., 2022).

The renewable energy scenery in South Asia is marked by both high potential and considerable challenges. The region is rich in renewable energy sources and features a wide range of energy profiles. The patterns of renewable energy adoption consumption across the region are not uniform and are influenced by the interplay of a myriad of factors from economic, social to technological. For example, India has emerged as one of the global leaders, making huge investments in their renewable energy infrastructure mainly solar and wind power (Kumar et al., 2023). Renewable energy sources have a combined installed capacity of 203+ GW. According to Invest India (n.d.), as of October 2024 India's renewable energy sources, have a combined installed capacity of 203 GW which comprises 92.19 GW Solar Power and 47.71 GW Wind power. Achieving the target of 40% installed electric capacity from non-fossil fuels by 2021, it is now aiming at 50% by 2030 (Invest India, n.d. and IEA, 2023b). However, Bangladesh has had many difficulties when adopting these alternate sources of power because they still rely on traditional sources of energy majorly. Indeed, despite efforts to increase electrical access by using some fraction from renewables so far 90% of electricity production comes from fossil fuels in Bangladesh (IEA, 2023a). Although share of renewable energy in electricity generation of Pakistan (24.7%) is greater in that case, renewables as final energy consumption is still low (7.12%) (IEA, 2024a). Nevertheless, Sri Lanka is in a good move. In 2021, their renewable energy consumption as a share of final energy consumption was 29.29% and renewables accounted for 50.3% of total electricity generation (IEA, 2024b). They are also expecting to be carbon neutral by 2050. These countries are also experiencing growing economy for the last couple of decades where energy plays a significant role. As the economy expands, balancing sophistication and efficiency at the production level and producing more complex goods is a crying need for complementing steady growth rate. Here, economic complexity acts as a crucial policy tool.

Economic complexity, defined as the collective knowledge embedded in a country's productive capabilities represents a compelling concept to understand the diverse ways through which countries develop and consume renewable energy (Hidalgo and Hausmann, 2009). It can also be described as the degree of economic sophistication and structural transformation within a country (Doğan et al., 2020). It also includes technological know-how, skills, advanced technologies, and innovative mechanism for efficiency. The economic complexity index is being widely used as the measure of magnitude of country's capacity to produce more complex products based on research and development that uses less energy being more environment friendly. Countries with higher economic complexity are often characterized by advanced industries, greater technological capabilities, and higher proportion of skilled workforce, all of which are crucial for the development and implementation of renewable energy technologies. According to Can and Gozgor (2017) and Apergis et al. (2018), during the development phase, economic complexity gradually increases by the cost of environmental degradation, consuming more fossil fuels. With the passage of time, the importance of environmental conservation gets increased. Then energy consumption habits gradually change and lead to the use of renewable energy. Overall, though the initial impact of economic complexities could be negative, with the time changes it mechanizes to develop more renewable-intensive infrastructures for both production and consumption to have a more sustainable environment. Hence, the capacity to innovate and adapt to new energy paradigms is therefore closely linked to a nation's economic complexity.

Studies on the impact of economic complexity on renewable energy consumption are still growing. Some (Rafique et al., 2021; Can and Ahmed, 2022; Salimi et al., 2023; Taghvaee et al., 2024;) find a positive impact whereas others (Li et al., 2021; Kazemzadeh et al., 2022; Adekoya et al., 2023; Chu, 2023) shows adverse impact. This clearly demonstrates ambiguity in this aspect and the scope for further study. Adding to that, to the best knowledge of the authors there are no papers that discussed this issue regarding the South Asia region. In that case, this study contributes to existing literature in multiple ways. Firstly, this research proposed to fill a gap in existing literature with a concentration on South Asian countries, this focus addresses the energy and economic characteristics of developing countries in this region. Secondly, we examine the relationship between economic complexity and renewable energy consumption by controlling major macroeconomic variables like GDP growth, total fossil fuel consumption, financial development, trade openness, and FDI which other studies failed to address aggregately. Thirdly, with a robust estimation methodology combining PMG and CCEPMG, it aims to have a panel estimation taking into account global common factors, endogeneity, and mixed integration order. Lastly, the Dumitrescu-Hurlin Panel Causality Test has been applied to explore the existence and direction of causality among variables. The study further addresses the inertia effect of economic complexity which provides insights into its multiple roles in driving energy intensity and the adoption of renewable energy which has been underexplored in the literature, particularly in the context of South Asia's developmental stage. Overall, this study aims to promote SDG 7.2.1 which entails increasing renewable energy share in total final energy consumption through its finding and policy suggestions.

The rest of the paper is organized as follows. We present a review of the current literature on economic complexity and renewable energy consumption in section 2. Section 3 details the data, model, and methods. In section 4, we present our results and discussion. Conclusion and policy recommendations are provided in section 5.

2. Literature Review

Though there exists a good number of scholarly works on the relationships between energy intensity and economic complexities (Kazemzadeh et al., 2023; Chu et al., 2024), carbon footprint and economic complexities (Doğan et al., 2020; You et al., 2021; Khezri et al., 2021; Taghvaee et al ., 2022; Zhang et al., 2023; Wahyudi et al., 2023; Ullah et al., 2024), EKC hypothesis and economic complexities (Adebayo et al., 2021; Balsalobre-Lorente et al., 2021; Agozie et al., 2022; Numanet al., 2022), and energy efficiency and economic complexities (Fang et al., 2021; Payne et al., 2023; Djeunankan et al., 2023), the research interest in the nexus between economic complexities and renewable consumption is still growing.

The study of Rafique et al. (2021) can be considered a pioneer in this arena. They studied the relationship for G7 and E7 countries (Developed and Emerging countries) time spanning 1990 to 2017. Using estimation techniques like FGLS, system GMM, FMOLS, and DOLS, they revealed that 1% increase in economic complexity tends to raise renewable energy demand by 0.71% for G7 and 1.65%

for E7 countries. The suggested renewable energy to be used as a policy factor or tool for sustainable environment. This result is supported by Taghvaee et al. (2024) in a different way. In their study, economic complexity is explored as energy-intensive complexity for the MENA region where it increases energy intensity. Due to energy-richness, MENA countries are motivated in energy-intensive diversification. This leads to an increase in overall energy demand where scope for renewable energy consumption also gets boost up. It was also supported by the estimated positive relationship between both variables. This overall process is regarded as the "inertia effect" of energy-intensive complexity in their study. Can and Ahmed (2022) tested the impact of economic complexity on renewable and non-renewable energy consumption for 14 European countries, covering the period from 1990-2017. Their estimation depicts that economic complexity reduces non-renewable energy consumption whereas it increases renewable energy consumption. They also found unidirectional causality between economic complexity and non-renewable energy consumption which runs from the former one and a bi-directional causal relation between economic complexity and renewable energy consumption. Therefore, for expanding complex activities, quality education was suggested as a vital instrument since economic complexity is all about knowledge sophistication. In addition, collaboration between academia and the private sector for more rigorous research and tax exemption in importing renewable energy-related technologies were also considered as key aspects to work on. Salimi et al. (2023) employed ARDL to assess the relationship of both previously mentioned variables for Iran, using the period between 2008 and 2018. They came up with a positive and significant relation between economic complexity and renewable energy. They urged to promote economic complexity and diversity to bolster technological and innovative capacities which turns the energy consumption choice from fossil fuels to renewable energies.

The adverse impact of economic complexity on renewable energy consumption is also observed in some studies. Using data of 94 countries, Adekoya et al. (2023) found that increasing economic complexities reduces renewable energy consumption regardless of the state of the development of the countries. Instead of disaggregating the countries into different economic groups; Advanced, Emerging, and Developing, the same result gets popped out. The reason behind it was explained that during the time of expanding structural components, a country needs more energy to keep its production wheel running. In this circumstance, fossil fuel is chosen over renewables due to its commercial viability and cost-efficient nature. Besides, lacking renewable-intensive energy infrastructure, inefficient technological knowledge, high maintenance cost, and adverse weather influence are also some well-argued reasons behind it. To mitigate this, Li et al (2021) posit that removing technical and market barriers and thinking of the world as a global village, ensuring regional balance, and aligning the policies with needs, capacity, and environment could be useful components. Adekoya's finding aligns with Chu (2023), where he examined the relationship for G7 countries. Though his investigation clearly states that economic complexities hamper renewable energy consumption, more investment and development in renewables gradually alleviate the negative impact. Kazemzadeh et al. (2022) also illustrate a similar result. They used data for 49 countries from 1985 to 2017. The ECI index has a negative impact in the first period and for the rest, it becomes positive (though the coefficients were not significant). However, they admitted that economic complexity brings newer technologies to production to increase productivity and efficiency which leads to an overall decrease in energy consumption. The findings of Alvarado et al. (2021) tell the same story. Analyzing data for 18 Latin American countries for the period 1995 and 2017, they showed that an increase in unit of economic complexity leads to a decrease, ranging from -0.08 to -0.01, in renewable energy consumption.

With this discussion above, it can be clearly stated that there still exists ambiguity in the role of economic complexity as a driver of renewable energy consumption in the existing literature. Moreover, in the case of the South Asian region, the direction of this nexus is still unknown. Hence, the authors complement this gap by taking into consideration major macroeconomic variables like GDP growth, total fossil fuel consumption, financial development, trade openness, and FDI.

3. Data, Model, and Methods

3.1 Data Set

The study uses data of 4 Asian countries from 1990 to 2021 to study the effect of economic complexity (ECI), Economic Growth (GDPG), Non- Renewable Energy Consumption (TFFC), Financial Development (FD), Trade Openness (TO), and Foreign Direct Investment (FDI) on Renewable Energy Consumption (RENE). Here, the four countries are; Bangladesh, India, Pakistan, and Sri Lanka. Due to scant data for the two key variables (economic complexity and renewable energy), other countries of South Asia are not considered for this study.

The time scope is based on the lean data availability of the main variables in this study which are economic complexity and renewable energy. All data are sourced and collected from the International Monetary Fund (IMF) database, the World Development Indicator (WDI) of the World Bank, and the Organization for Economic Co-operation and Development (OECD) database, table 1.

Table 1: Descriptions and Sources of Variables

Variables	Descriptions	Sources
RENE	Renewable energy consumption (% of total final energy consumption)	WDI (2021)
ECI	Economic Complexity Index	OEC (2021)
GDPG	Gross Domestic Product Growth	WDI (2021)
TFFC	Total Fossil Fuel Consumption	EIA (2021)
FD	Financial Development Index	IMF (2021)
TO	Trade (% of GDP)	WDI (2021)
FDI	Foreign direct investment, net inflows (% of GDP)	WDI (2021)

3.2 Empirical Model

Using data from 4 Asian countries, this study investigates the factors that affect renewable energy consumption both in the short run and long run. Following (Rahman et al., 2023), the functional form of the model to be estimated is;

$$RENE_{it} = f(ECI_{it} \,; GDPG_{it} \,; TFFC_{it} \,; FD_{it} + TO_{it} \,; FDI_{it}) \tag{1}$$

The logarithmic function of equation 1 can be expressed as follows

$$LNRENE_{it} = \alpha + \pi_1 ECI_{it} + \pi_2 GDPG_{it} + \pi_3 LNTFFC_{it} + \pi_4 FD_{it} + \pi_5 TO_{it} + \pi_6 LNFDI_{it} + \mu_{it} \tag{2}$$

Where RENE is renewable energy consumption and is referred to as the dependent variable, the independent variables ECI, GDPG, TFFC, FD, TO, and FDI mean economic complexity, economic growth, non-renewable energy consumption, financial development, trade openness, and foreign direct investment, respectively. Additionally, α is the constant μ is the stochastic term and i and t refers to countries and time in the panel series respectively.

3.3 Estimation Procedure

To achieve the objectives of the study, we perform the pre-estimation test and the estimation. For each series in the model, the cross-sectional dependence (CSD) and the unit root were examined. The study also adopted different methods to report cross-sectional dependence and different orders of integration in the panel series. Also, Co-integration tests were performed on the variables used in the study. The study further examined the short-run and long-run estimates to achieve the main objective of the study using different methods like the Pooled Mean Group (PMG) and Common Correlated Effect Pooled Mean Group (CCEPMG). The study further examined the causal relationship among the variables by making use of the Dumitrescu-Hurlin Panel Causality Test.

3.3.1 Cross-Sectional Dependence and Unit Root Test

It is important to carry out the pre-estimation test which determines the estimation technique to use in achieving the objectives of the study. The CSD and the unit root tests will be fundamental to determining the estimation technique for the panel regression. According to (Ertur & Musolesi, 2017; Rahman et al., 2023), a panel estimation result can be spurious or inconsistent if the CSD is disregarded. Therefore, the study makes use of the Breusch-Pegan LM (1980) and Pesaran CD (2004) methods to estimate the CDS. The two methods can be used in the case of a balanced panel and the use of the Breusch-Pegan LM (1980) is put forward when the time scope (T) is greater than the number of cross-sections (N). In the case of both tests, we reject the null hypothesis and conclude that the series exhibits CSD when the P-value is less than 0.05 i.e. ($P \leq\ 0.55$). The econometric model of the tests is given as:

$$\text{Breusch} - \text{Pagan LM test} = y_{it} = \gamma_0 + \gamma_1 X_{it} + \mu_{it} \tag{3}$$

$$\text{Pesaran (2004) CD test} = \sqrt{\frac{2T}{N(N-1)}} \sum_{i-1}^{N-1} \sum_{j=i+1}^{N} \rho_{ij} \tag{4}$$

In equation 4, T and N are the number of time periods and number of cross-sectional units respectively. While ρ_{ij} is the estimated correlation coefficient of the residuals between i and j.

To check for stationarity in the panel series, the study makes use of the first generation and the second-generation unit root tests. The unit root tests adopted are the Fisher ADF and the Cross-Sectional IPS by Im, Pesaran and Shin (IPS) (2003). Literature shows that the CIPS test proposed by (Pesaran, 2006) for panel unit tests is superior to other panel unit root tests because IPS and ADF depend on the assumption of cross-sectional independence, however, studies have shown that this does not always hold because it does not consider the possibility of cross-sectional dependence.

The econometric model of the CIPS:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} t_{iT} \tag{5}$$

In equation 5, t_{iT} means the ADF t-statistic that is derived from the regression for the unit i and T. N is therefore the number of cross-sectional units.

3.3.2 Panel Co-integration Tests

Following the estimation of the panel unit root tests, the study further makes use of different co-integration tests which are the (Pedroni, 2004), test, and (Kao, 1999) test. The Westerlund (2007) is more efficient for the case of CDS, also, the Pedroni and Kao are conventional techniques, however, the study also adopted these methods to report more robust results. In these tests, the null hypothesis assumes no co-integration among the variables (Renewable energy Consumption, Economic Complexity, Gross Domestic Product Growth, Total Fossil Fuel Consumption, Financial Development, Trade, and, Foreign direct investment) in the 4 selected South Asia countries. The alternative hypothesis establishes co-integration which means that there is a long run relationship among the variables in the model.

3.3.3 PMG and CCEPMG

After the estimation of the panel unit root test and the co-integration test, the study makes use of the PMG to estimate the long run co-efficient as proposed by (Pesaran et al., 1999) In the instance of stationary series, where there is integration of different orders. The PMG is expected to have a lower heterogeneity because the approach allows for heterogeneity in the short run while homogeneity is achieved in the long run. This method also takes care of dynamic differences in the short run and treats long run relationships as consistent across the sample. The PMG method estimates the short run and the long run model. The PMG regression model is specified as follows:

$$\Delta Y_{it} = \emptyset_i \left(Y_{i(t-1)} - \beta_i X_{it}\right) + \sum_{j=1}^{p-1} \partial_{ij} \Delta Y_{i(t-j)} + \sum_{j=0}^{q-1} \gamma_{ij} \Delta X_{i(t-j)} + \mu_i + \varepsilon_{it} \tag{6}$$

From equation 6, Y_{it} is the dependent variable of units i in time t, while X_{it} and $\emptyset_i$ is the vector of independent variables for the unit i in time t and coefficient of the speed of adjustment for the unit i respectively. β is the vector of long run coefficients and is assumed to be homogeneous across units in the model. The coefficients of the lagged differences of the dependent variable are represented as ∂_{ij}, while γ_{ij} is used to get the coefficients of the lagged independent variables. μ_i is the individual-specific fixed effect, while the error term is ε_{it}.

Following the PMG model, the variables used in this study are further introduced into the model to estimate the short run and the long run parameters. Therefore, the PMG model to be used is re-represented and specified as equation 7.

From equation 7,

$\varphi_i\left(LNRENE_{i(t-1)} - \pi_1 ECI_{it} - \pi_2 LNGDPG_{it} - \pi_3 LNTFFC_{it} - \pi_4 FD_{it} - \pi_5 LNTO_{it} - \pi_6 FDI_{it}\right)$ is computed to capture the long run relationship between the dependent variable i.e. renewable energy consumption and the independent variables in the model. φ_i is the speed of adjustment parameter which tells how quickly the deviations from the long run equilibrium adjust or are corrected. In the short run dynamics of the model, the summations terms which involves ω_{ij} and γ_{mik} measures the short run effects of the past values the dependent variable and the independent variables. The essence of the short run model is that it accounts for the immediate effects of changes in the independent variables on dependent variable. The error term or other factors that effects renewable energy consumption which are not accounted for in the model is represented by ε_{it}.

$$\begin{aligned}\Delta LNRENE_{it} = {} & \varphi_i\left(LNRENE_{i(t-1)} - \pi_1 ECI_{it} - \pi_2 LNGDPG_{it} - \pi_3 LNTFFC_{it} - \pi_4 FD_{it} - \pi_5 LNTO_{it} - \pi_6 LNFDI_{it}\right) \\ & + \sum_{j=1}^{p-1} \omega_{ij}\, \Delta LNRENE_{i(t-j)} + \sum_{k=0}^{q-1} \gamma_{1ik}\, \Delta ECI_{i(t-k)} + \sum_{k=0}^{q-1} \gamma_{2ik}\, \Delta LNGDPG_{i(t-k)} \\ & + \sum_{k=0}^{q-1} \gamma_{3ik}\, \Delta LNTFFC_{i(t-k)} + \sum_{k=0}^{q-1} \gamma_{4ik}\, \Delta FD_{i(t-k)} + \sum_{k=0}^{q-1} \gamma_{5ik}\, \Delta LNTO_{i(t-k)} + \sum_{k=0}^{q-1} \gamma_{6ik}\, \Delta LNFDI_{i(t-k)} \\ & + \sigma_1 + \varepsilon_{it}\end{aligned} \tag{7}$$

Furthermore, the study employed the method of Common Correlated Effects Pooled Mean Group (CCEPMG) proposed by Pesaran (2006), this method is an extension of the PMG model because it accounts for cross-sectional dependence in the panel unit. The method is particularly useful as it takes care of the limitations of the PMG which assumes cross-sectional independence among the panel unit. In the study of renewable energy consumption, there are common shocks such as shared environmental shocks like climate events, global trade policies, and energy prices which the PMG model does not handle properly. The CCEPMG therefore models these explicitly by including the cross-sectional averages of the dependent and independent variables. This method also helps to account for unobserved regional or global common factors that are liable to affect the panel units. While PMG presumes homogeneity in the long run and allows for heterogeneity in the short run dynamics across units in the panel, it does not model cross-sectional dependence, which may result from unobserved global common factors. The CCEPMG also solves this problem by including cross-sectional averages which provides a more robust and reliable estimation. Additionally, the CCEPMG also overcomes the problems on endogeneity, and it can also handle mixed integration order.

The econometric model for CCEPMG is specified as:

$$\Delta LNRENE_{it} = \varphi_i\big(LNRENE_{i(t-1)} - \pi_1 ECI_{it} - \pi_2 LNGDPG_{it} - \pi_3 LNTFFC_{it} - \pi_4 FD_{it} - \pi_5 LNTO_{it} - \pi_6 LNFDI_{it} - \pi_7 \overline{LNRENE}_{t-1} - \pi_8 \bar{X}_{it}\big) + \sum_{j=1}^{p-1} \omega_{ij}\, \Delta LNRENE_{i(t-j)} + \sum_{k=0}^{q-1} \gamma_{mik}\, \Delta X_{i(t-k)} + \mu_{it} \quad (8)$$

From the equation 8, $\overline{LNRENE}_{t-1}$ and $\bar{X}_{it}$ captures the cross-sectional averages of the dependent variable and the independent variables, respectively in the model. This is set up in the model to capture the regional and global common factors that can pose an issue in the units. The other component in the model is similar to the PMG model, φ_i and π captures the speed of adjustment and the long-run coefficients respectively. The short run dynamics are captured by ω_{ij} and γ_{mik}.

4. Result and Discussion

Results of cross-sectional dependence reported in table 2. P values for both tests are lower than 5% stating that null hypothesis of cross-sectional independence is rejected. As a result, it confirms the presence of cross-sectional dependence in the estimated model.

Prior to estimating the long relationship among variables, it is essential to check their stationarity properties. Two widely accepted unit root tests, ADF and CIPS, are employed for this purpose, in table 3 and 4. Results from both analysis shows consistency in terms of stationarity level. Stationarity level of almost all variables is similar in both tests. RENE, ECI, TFFC, and TO are integrated at I (1) and GDPG and FDI are integrated at I (0). However, in ADF FD becomes stationary after taking first difference and in CIPS it remains stationary at level.

To understand the existence of long run relationship, checking for cointegration is a prerequisite. Table 5 reports the result of Kao, Pedroni and Westerlund cointegration tests. As most of the statistics are statistically significant, null hypothesis of no cointegrating relationship can be rejected. This leads to a conclusion that, there exists long run relationship among the variables.

The results of the Hausman test are presented in Table 6 to choose between MG and PMG model and CCE-MG and CCE-PMG model. The null hypothesis for this analysis is PMG (CCE-PMG) is a consistent and more efficient estimator than MG (CCE-MG). Since the value of both chi-square is 3.58

and 3.369 with a probability value of 0.7294 and 0.3812 respectively, the analysis result fails to reject the null hypothesis. Hence, it favors PMG over MG and CCE-PMG over CCE-MG.

Table 2: Cross-Sectional Dependence Test Result

Tests	Statistic	p-value
Pesaran CD	2.7254	0.006423
Breusch-Pagan LM	13.014	0.04281

Table 3: ADF Unit Root Test

	Level		First difference		Stationary
	t statistics	p-value	t statistics	p-value	
LN_RENE	-2.029	0.5645	-5.2404**	0.01	At first difference
ECI	-2.5049	0.3666	-6.4074**	0.01	At first difference
LN_GDPG	-3.2991**	0.0445	-3.9948**	0.01178	At level
LN_TFFC	-2.0919	0.5383	-4.4518**	0.01	At first difference
FD	-2.564	0.3421	-5.5713**	0.01	At first difference
LN_TO	-2.7103	0.2813	-3.7776**	0.02235	At first difference
LN_FDI	-3.5941	0.03664	-6.2549**	0.01	At level

***p < 0.01, **p < 0.05, and *p < 0.10.

Table 4: CIPS Unit Root Test

	Level	First difference	Stationary
LN_RENE	-2.3883794 (>0.10)	-3.9951115*** (<0.01)	At first difference
ECI	-2.2249831 (>0.10)	-4.0506577*** (<0.01)	At first difference
LN_GDPG	-2.40796** (<0.05)	-3.8250032*** (<0.01)	At level
LN_TFFC	-2.1247960 (>0.10)	-4.22424** (<0.01)	At first difference
FD	-3.10520** (<0.05)	-3.95711*** (<0.01)	At level
LN_TO	-1.37984 (>0.10)	-3.76209*** (<0.01)	At first difference
LN_FDI	-3.28091*** (<0.01)	-4.18825*** (<0.01)	At level

p-values are given in parenthesis. ***p < 0.01, **p < 0.05, and *p < 0.10.

Table 5: Result of Different Panel Cointegration Test

Kao test		
	Statistic	p-value
Modified Dickey-Fuller t	-0.2200	0.4129
Dickey-Fuller t	-0.6601	0.2546
Augmented Dickey-Fuller t	0.0751	0.4700
Unadjusted modified Dickey-Fuller t	-3.6718	0.0001
Unadjusted Dickey-Fuller t	-2.4820	0.0065

Pedroni test		
Modified Phillips-Perron t	0.9045	0.1829
Phillips-Perron t	-2.1991	0.0139
Augmented Dickey-Fuller t	-1.3806	0.0837

Westerlund test			
Statistics	Value of the Test	Z-value	p-value
G_t	-3.061	-2.104	0.018
G_a	-9.616	0.074	0.529
P_t	-5.721	-1.964	0.025
P_a	-10.293	-1.143	0.127

H_0: No cointegration
H_1: All panels are cointegrated

Table 6: Hausman Test

	Chi-square	p-value	Decision
MG vs PMG	3.589	0.7294	Favors PMG
CCEMG vs CCEPMG	3.369	0.3812	Favors CCEPMG

Table 7 reports the results of PMG and CCE-PMG estimations. Here, coefficients of error correction terms are negative and significant for both models. Hence it also demonstrates the existence of long run relationship among variables. In another words, the deviation from the run results could be corrected at a speed of 41% for PMG and 50% for the CCE-PMG model.

Both short run and long run estimations are also reported in Table 7. In the long run, coefficients of ECI in PMG and CCE-PMG are positive and significant, showing that economic complexity has a positive impact on renewable energy consumption. Quantitatively, renewable energy consumption will increase by 2.13 units (PMG) and 0.36 units (CCE-PMG) if there is a unit increase in economic complexity. This finding is in line with Rafique et al. (2021), Can and Ahmed (2022), and Salimi et al. (2023). When an economy is progressing, it is required to keep adopting newer innovations and technologies to produce more sophisticated services and goods and make the economy more efficient. To make this happen, economic complexity is essential which aggregates attributes, efficiency, skills, and technical expertise (Sun et al., 2022). It transforms a traditional economy into a sustainable one through innovation where efficiency matters. Besides, it will shift the country's dependency from fossil fuel energy consumption to renewable energy consumption encouraging a low-carbon economy (Doğan et al., 2020). In the case of South Asian countries, the scenario is slightly different. All of them are developing countries and highly active in economic actions for the past couple of decades. Their rapid economic growth mirrors their actions. More economic actions require more energy consumption when economic complexity increases (Can and Ahmed, 2022). Hence, diversification of energy sources is essential in these circumstances where renewable energy is a potential one. Taghvaee et al., (2024) analyze this phenomenon as the inertia effect of energy-intensive complexity. In this situation, economic complexity escalates energy intensity by raising overall energy demand as well as renewable energy due to technological sophistication.

Both GDP growth and fossil fuel consumption have a negative impact on renewable energy consumption in the long run. A 1% increase in GDPG leads to a decrease of 0.48% (PMG) and 0.03% (CCE-PMG) in renewable energy consumption. It supports the findings of Mahalik et al. (2023). These studies explained the reason behind that, which means South Asia's economy is at the initial phase of the EKC hypothesis. According to the EKC hypothesis, initially with the increase in economic growth, the demand for a sustainable environment decreases. However, the demand increases gradually with time. In South Asia, though most of the countries are enjoying rapid growth, they encounter problems like poverty and unemployment which lead their production mix to be more economic-centric than the environment. Besides, consuming fossil fuels is more economical. That drives toward giving less importance to renewable energy consumption. In addition to that, results from Table 7 depict that raising fossil fuel energy consumption has a negative impact on renewable consumption in the PMG model. RENE decreases by 0.46% if TFFC increases by 1%. This is in line with Kazemzadeh et al. (2023). Nevertheless, the CCEPMG shows a dissimilar scenario where there exists a positive relationship.

Financial development does not have a significant relationship with renewable energy consumption in the long run. However, the coefficients of trade openness show an interesting finding. In the PMG model it indicates no significant relationship, whereas in the CCE-PMG model, it has a negative and significant relationship with renewable energy consumption. It implies that most of the traded goods are manufactured by consuming non-renewable energy (Han et al., 2022). So, with the increasing volume of trade, they increase their dependency on fossil fuel intensive production. Foreign direct investment has a positive impact on renewable energy in both models. This result aligns with Qamruzzaman and Jianguo (2020). Foreign direct investment endorses renewable energy through the insertion of renewable-intensive capital and technologies in the economy (Kor and Qamruzzaman, 2023). Along with that, it brings factors like knowledge sharing and market expansion which encourages renewable energy consumption (Shah et al., 2022).

Table 7: Results of PMG and CCEPMG Model

Dependent Variable: LN_RENE Lag order: 2 2 3 3 1 3 1				
	PMG		**CCEPMG**	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Short run				
(Intercept)	-0.057271*	0.093962	—	
D (LN_RENE)	-0.027380***	0.016039	—	
D (ECI)	0.015337	0.041353	0.05833**	0.02212
D (LN_GDPG)	0.007066**	0.025887	0.15833***	0.05312
D (LN_TFFC)	-1.339321***	0.319697	-0.06217**	0.03158
D (FD)	0.375374	0.240226	-0.04217	0.01958
D (LN_TO)	0.125204	0.171992	0.12850	0.04673
D (LN_FDI)	0.017662	0.028172	0.07283**	0.02812
Error correction term	-0.41283***	0.07592	-0.50012***	0.01012
Long run				
(Intercept)	-0.006618**	0.304363	-5.0015**	0.1413
ECI	1.137660***	0.188153	0.3097**	0.0990
LN_GDPG	-0.475400***	0.145397	-0.0257*	0.0146
LN_TFFC	-0.463755***	0.103341	0.0882***	0.0047
FD	2.421946	1.280476	-0.1374	0.3416

LN_ TO	-0.364814	0.331576	-0.0015***	0.0004
LN_FDI	0.314677***	0.094497	0.0275	0.0372
ECI_avg	—		-1.0097**	0.1277
LN_GDPG_avg	—		0.0257*	0.0159
LN_TFFC_avg	—		-0.0882	0.0759
FD_avg	—		0.1374	0.8975
LN_ TO_avg	—		0.0015	0.0012
LN_FDI_avg	—		-0.0275*	0.0163
LN_RENE_avg	—		1.0000*	0.8286

Breusch-Godfrey Test for the autocorrelation in residuals				
LM test	0.70769	p-value	0.5025	
Ljung-Box Test for the autocorrelation in residuals				
X-squared	0.051353	p-value	0.8207	
Breusch-Pagan Test for the homoskedasticity of residuals				
BP	38.621	p-value	0.1089	

***p < 0.01, **p < 0.05, and *p < 0.10.

In terms of the coefficients' nature (positive and negative), the short run estimations are quite similar to the long run though there exists a difference in significance level. Only GDPG turns out to have a positive impact which has an adverse impact in the long run. As the study's prime concern is to discuss long run estimations, here the short run result is not described thoroughly.

Table 8 provides the result of the panel causality test. The findings show that there is a two-way causality run from ECI and TFFC to RENE. Likewise, a unidirectional causal relationship is found between TO and RENE. The estimated long run results also support these causal directions. On the one hand, ECI and FDI granger cause FD. On the other hand, there exists a one-way causality between GDPG and FDI.

Table 8: Dumitrescu-Hurlin Panel Causality Test

Null Hypothesis	Ztilde	p-value	Conclusion
ECI doesn't Granger-cause LN_RENE	1.9929	0.04627	ECI ↔ RENE
LN_RENE doesn't Granger-cause ECI	8.0879	6.07e-16	
LN_GDPG doesn't Granger-cause LN_RENE	-1.1691	0.2424	GDPG ≠ RENE
LN_RENE doesn't Granger-cause LN_GDPG	-0.33741	0.7358	
LN_TFFC doesn't Granger-cause LN_RENE	4.4754	7.625e-06	TFFC ↔ RENE
LN_RENE doesn't Granger-cause LN_TFFC	9.271	2.2e-16	
FD doesn't Granger-cause LN_RENE	1.1686	0.2426	FD ≠ RENE
LN_RENE doesn't Granger-cause FD	-0.21851	0.827	
LN_TO doesn't Granger-cause LN_RENE	2.0371	0.04164	TO → RENE
LN_RENE doesn't Granger-cause LN_TO	-0.20328	0.8389	
LN_FDI doesn't Granger-cause LN_RENE	-0.10337	0.9177	FDI ≠ RENE
LN_RENE doesn't Granger-cause LN_FDI	0.036498	0.9709	
LN_GDPG doesn't Granger-cause ECI	-1.0543	0.2918	GDPG ≠ ECI
ECI doesn't Granger-cause LN_GDPG	-0.41526	0.678	
LN_TFFC doesn't Granger-cause ECI	1.3676	0.1714	TFFC ≠ ECI
ECI doesn't Granger-cause LN_TFFC	-0.41815	0.6758	
FD doesn't Granger-cause ECI	-0.50391	0.6143	FD ← ECI
ECI doesn't Granger-cause FD	4.0658	4.787e-05	
LN_TO doesn't Granger-cause ECI	0.89468	0.371	TO ≠ ECI

ECI doesn't Granger-cause LN_TO	-0.41781	0.6761	
LN_FDI doesn't Granger-cause ECI	0.27644	0.7822	FDI ≠ ECI
ECI doesn't Granger-cause LN_FDI	-0.33663	0.7364	
LN_TFFC doesn't Granger-cause LN_GDPG	1.1727	0.2409	TFFC ≠ GDPG
LN_GDPG doesn't Granger-cause LN_TFFC	0.82001	0.4122	
FD doesn't Granger-cause LN_GDPG	-1.1284	0.2591	FD ≠ GDPG
LN_GDPG Granger-cause FD	0.54644	0.5848	
TO Granger-cause LN_GDPG	-0.48878	0.625	TO ≠ GDPG
LN_GDPG Granger-cause TO	-0.98894	0.3227	
LN_FDI Granger-cause LN_GDPG	0.061693	0.9508	FDI ← GDPG
LN_GDPG Granger-cause LN_FDI	5.1628	2.433e-07	
FD Granger-cause LN_TFFC	-0.15539	0.8765	FD ≠ TFFC
LN_TFFC Granger-cause FD	1.4586	0.1447	
LN_TO Granger-cause LN_TFFC	1.1902	0.234	TO ≠ TFFC
LN_TFFC Granger-cause LN_TO	-0.62692	0.5307	
LN_FDI Granger-cause LN_TFFC	0.53293	0.5941	FDI ≠ TFFC
LN_TFFC Granger-cause LN_FDI	-0.71698	0.4734	
LN_TO Granger-cause FD	0.7805	0.4351	FD ≠ TO
FD Granger-cause LN_TO	0.89312	0.3718	
LN_FDI Granger-cause FD	3.6565	0.0002557	FD ← FDI
FD Granger-cause LN_FDI	1.4502	0.147	
LN_FDI Granger-cause LN_TO	-0.11396	0.9093	TO ≠ FDI
LN_TO doesn't Granger-cause LN_FDI	1.6743	0.09407	

5. Conclusion and Policy Recommendations

The present study examines the relationship between economic complexity, economic growth, non-renewable energy consumption, financial development, trade openness, and foreign direct investment (FDI) on renewable energy consumption, using data from four countries in South Asia spanning 1990 to 2021. The study employs the PMG and CCE-PMG methods. The results successfully revealed that in the long run, the coefficients of economic complexity in both PMG and CCE-PMG are positive and significant. Thus, indicating that economic complexity positively impacts renewable energy consumption. As an economy becomes more mature, it needs to adopt latest innovations and technologies to produce more sophisticated goods and services, thereby increasing efficiency. However, South Asian economies hold energy intensive economic complexities but their impact is green. Hence, their economic complexities urge for more renewable energy consumption. Secondly, GDP growth and fossil fuel consumption have a negative impact on renewable energy consumption in the long run. Third, financial development shows no significant relationship with renewable energy consumption in the long run. The increasing volume of trade has led to a higher dependency on fossil fuel-intensive production which could be a problem in the long term. Last, the present result's findings confirm a two-way causality between economic complexity and non-renewable energy consumption on renewable energy consumption. There is also a unidirectional causal relationship between trade openness and renewable energy consumption. The estimated long-run results support these causal directions. Additionally, economic complexity and FDI granger-cause financial development, while a one-way causality is observed between GDP growth and FDI.

Based on the results, several key policy recommendations can be made to promote renewable energy consumption. First, South Asian countries should encourage economic complexity which is very essential for driving innovation in renewable energy and also to promote sustainable economic growth. Governments can give more incentives in R&D and offer incentives like tax and subsidies to companies working on specific renewable technologies. Overall, they should restructure their economies, transitioning from fossil fuel dependent to renewable, to become green and sustainable. For example, the government can patronize and incentivize economically complex sectors, those that are energy efficient and promote green energy consumption. Second, new economic zones dedicated to sustainability could be established to encourage entrepreneurs producing sustainable and environment-friendly products. This will also result in more internal investment and foreign capital flow in that zone and ultimately lead towards green growth. Third, policy for turning the manufacturing sectors greener by increasing renewable energy's ratio in their energy consumption mix gradually, could be an effective leap towards it. Promoting net metering system could also be an impactful move. These initiatives could give a strong political will in supporting the private sector to be more aware in the environment. Fourth, research on dynamic infrastructure for energy consumption should be prioritized, which could convert its energy consumption pattern from fossil to renewable with cost efficient nature. Fifth, South Asian countries should support policies such as carbon taxes, removing fossil fuel subsidies, and investing in green infrastructure which can help reduce fossil fuel dependence. Sixth, promotion and investment in infrastructure related to circular economy practices should also be encouraged by relevant policy tools and incentives. Seventh, Public-Private Partnership (PPP) should be promoted to attract investment in renewable infrastructures. Eighth, FDI also plays a key role in renewable energy expansion. So, the government of South Asia should attract foreign investment by offering incentives and simplifying regulations around renewable energy projects. Although financial development doesn't directly impact renewable energy consumption in the long run, enhancing green financing options like green bonds can still support the sector. Lastly, the government of South Asian countries should help industries heavily dependent on fossil fuels transition to cleaner energy through support programs, retraining workers, and offering incentives to businesses that adopt renewable alternatives.

The limitations of the present study include its reliance on macro and aggregate data, which provide less detailed insights at the micro level. Future research could benefit from breaking down the analysis by industry, potentially revealing more nuanced and interesting findings. Future research could accommodate this limitation of the study by using firm level data or household data in order to give more comprehensive and complex results.

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Data set will available upon request.

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