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Grid Resilience and Green Transformation: Investigating the Synergy of Economic, Technical, and Policy Factors in Renewable Integration in South Asia

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Abstract: *Electricity is known as the engine of economic progress and development, but the source of energy use has a profound impact on environmental degradation. Indeed, clean energy significantly reduces greenhouse gas emissions and pollution, whereas traditional energy has numerous costs, such as environmental degradation, health issues, and depletion of energy sources. The study examines the impact of technical, economic, and policy factors on grid resilience in South Asian economies from 2000-2023, revealing a significant correlation between these factors. The Kao cointegration test verifies a long-run association among variables and underscores the interdependence of technical, economic, and policy magnitude. In fact, the outcomes of FMOLS and DOLS reveal that increased investment in renewable energy and improved renewable energy capacity considerably decrease electricity distribution losses and strengthen grid resilience. Conversely, higher CO_2 emissions negatively influence grid efficiency and sustainability. Policy factors, deliberate through the Country Policy and Institutional Assessment (CPIA), reveal the vital role of robust environmental policies and institutional frameworks in falling vulnerabilities and improving grid consistency. The study suggests targeted interventions, including planned investments in renewable energy infrastructure, embracing advanced technical solutions, and policy and institutional restructuring, to strengthen grid resilience and ensure sustainable electricity distribution in the region. These are essential for authorities, stakeholders, policymakers, and stakeholders determined for long-term energy reliability and sustainability.*

Key Words: Renewable Energy (RE), Renewable Energy Capacity (REC), Non-Renewable Energy (NRE), Fully-Modified Ordinary Least Square (FMOLS), Dynamic Ordinary Least Square (DOLS)

Introduction

The urgent need for transition to renewable energy sources has become a crucial global imperative, particularly as countries face the dual challenges of climate change and ensuring energy security. Every nation of the World strives to achieve sustainable development objectives and combat climate change. The resilience of power grids is a foundation stone for transitioning to renewable energy systems, permitting the integration of miscellaneous energy sources like solar and wind while maintaining energy reliability. (Aziz et al., 2024). As the world faces issues of growing energy demands, infrastructure development, and dire climate challenges, the transition to renewable electricity is a crucial component of green transition without interception. In South Asia, a region characterized by a rapidly growing population, urbanization, and escalating energy demands, the incorporation of renewable energy into the grid is essential for achieving a sustainable green transformation. Mainly, the integration is a concept of grid resilience, which refers to the capacity of the electricity grid to withstand and improve disruptions, maintaining a reliable power supply even during unfavorable conditions (Kumar et al., 2021).

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Indeed, energy requirements in South Asia are predicted to be boosted significantly due to rapid economic growth and urbanization. According to the IEA, 2022, energy consumption in South Asia is predicted to enhance by 6 percent every year till 2030. India, as the largest energy consumer in the region, accounts for around 74.04 percent of South Asia's total energy use (World Bank, 2023). This increasing energy demand shows a formidable challenge in integrating renewable energy sources. As of 2023, renewable energy sources add about 15% to South Asia's energy mix, which is a huge increase from just 5.04 percent in 2010; nevertheless, this figure remains below the recommended 40 percent target for sustainable growth (Asian Development Bank 2023). Therefore, these dire challenges reveal that an energy transition is necessitated, especially by enchasing grid resilience to support the growing production of electricity from renewable sources while diminishing electricity distribution losses. According to the World Bank report, 2020 shows that the current average is around 20 percent, which is a distribution loss in the region. This distribution loss not only shows inefficiencies within the grid but also undermines the likely benefits of renewable integration by restricting the effective delivery of generated electricity.

Undeniably, sustainable economic factors are very crucial in reshaping the pace and scale of renewable energy embraced across South Asia. The region has faced a marked increase in investments in renewable energy, with India alone attracting approximately $11.18 billion in green energy investments in 2022 (World Bank, 2023). Despite this development, smaller countries like Pakistan and Bangladesh have also struggled to secure similar levels of investment due to various financial crises, including high debt, capital costs, and volatility of currency. For instance, the cost of solar energy in India has reached a record low of $0.03 per kilowatt-hour as of 2020. This reflects the sector's growing economic progress when supported by favorable investment conditions and competitive bidding processes (International Renewable Energy Agency [IRENA], 2021). In contrast, smaller countries in South Asia often face higher energy costs and limited financing choices, primarily due to their reliance on energy imports and the lack of large-scale domestic development. This economic context emphasizes the need for tailored financial strategies and regional cooperation to foster investment in renewable energy projects, improve grid resilience, and reduce electricity distribution losses.

Similarly, the technical factors influencing grid resilience are equally significant, particularly concerning advancements in grid infrastructure and energy storage technologies. The existing grid systems in South Asia face considerable challenges in accommodating the irregular nature of renewable energy sources like wind and solar. The ADB reports show that although India has a renewable energy capacity of 122 GW, only a fraction of this capacity can be effectively integrated into the grid due to restrictions in transmission infrastructure and insufficient storage solutions (ADB, 2023). As of 2023, energy storage constitutes less than 2 percent of South Asia's energy mix, compared to a global average of 15 percent (IEA, 2023). This underdevelopment poses grave challenges to maintaining grid stability and reliability in the face of variable renewable generation. Hence, improvement in grid infrastructure and investment in higher energy storage space technologies, such as lithium-ion batteries and pumped hydro storage, are essential steps in enhancing grid resilience. These investments in renewable electricity production will facilitate better integration of renewable energy sources, ensuring that the grid can manage supply fluctuations and provide reliable electricity during peak demand periods, thereby reducing distribution losses and improving overall grid efficiency (Usman et al., 2024).

Moreover, policy strategies also play a vital role in fostering an environment conducive to renewable energy growth and improving grid resilience. India’s striving aim of achieving 500 GW of renewable energy capability by 2030 highlights the country's commitment to clean energy integration, supported by initiatives like the National Solar Mission and various wind energy programs (Government of India, Ministry of New and Renewable Energy, 2023). In contrast, Pakistan aims for a 30% renewable energy share in its overall energy mix by 2030 but faces significant challenges in aligning its policies with necessary infrastructure and investment needs (Pakistan Ministry of Climate Change, 2022). According to a comparative study by the World Bank (2022), India has significantly improved project approval timelines, reducing them from 24 months to just 12 months, facilitating faster deployment of renewable energy projects. Other South Asian countries, however, continue to struggle with bureaucratic inefficiencies and regulatory hurdles, impeding the scalability of renewable energy projects. Harmonizing policies and enhancing incentives for renewable energy development are critical steps to accelerate the transition and promote grid resilience by effectively managing electricity distribution losses (Bagherian et al., 2020).

Put into brief, the path to achieving a green transformation in South Asia relies on comprehensive indicators that drive grid resilience—especially in terms of electricity distribution losses—and renewable energy integration. The aim of this analysis is to empirically investigate grid resilience and green transition by addressing the synergy of economic, technical and policy factors.

Literature Review

Energy is known as the engine of economic growth and development; without affluent energy sources, one can't progress efficiently. However, in the era of depleting nonrenewable energy sources and climate change issues, the world is transforming toward alternative renewable energy sources, and grid energy is one of them. Grid resilience plays a basic role in the transition toward clean energy, especially in regions with flashing energy sources like solar and wind. Lund et al. (2015) highlight the resilience of the grid ensures a constant energy supply without any disruptions, making it necessary for renewable incorporation. The use of advanced technologies like smart grids, demand reaction systems, and energy storage improves grid flexibility and consistency, which are vital for managing renewable energy unpredictability. In South Asia, grid resilience remains an issue due to obsolete infrastructure, leading to affluent transmission and distribution victims (IRENA, 2022). Regardless of development in countries such as India, which has commenced the National Smart Grid Mission, the nearest countries also require high investments in grid advancement to achieve parallel results.

Additionally, economic factors play a crucial role in the development of grid resilience and modernization. According to Apergis and Payne (2011), economic development plays a dual role; it increases energy demand and offers affluent resources for renewable energy transition. In South Asia, fast industrialization has increased energy consumption and climate change issues; it could be taken with renewable energy in order to mitigate energy demand and environmental impacts (Bhattacharya et al., 2016). Inequality in economic development within the region generates unequal progress in renewable implementation and grid reconstruction. Evidence recommends that economies with higher GDP, such as India, invest extra in renewable energy development and grid infrastructure, increasing their resilience and efficiency to modernize renewable energy sources (IRENA, 2022). Furthermore, economic planning, such as fiscal stimulus and tariffs, has been effective in escalating renewable energy adoption. Therefore, their adaptation of grid resilience varies considerably across South Asian countries, showing the region's diverse economic scenario.

Moreover, clean and green policy initiatives also play a crucial role in reshaping grid resilience and enhancing renewable energy transformation. Shukla et al. (2017) emphasize that renewable energy aims, add-in tariffs, and energy reliability are involved in the modernization process. In South Asia, India's motivation toward policy frameworks, consisting of the National Electricity Plan, intends to attain 50% renewable capability by 2030, while Bangladesh's Renewable Energy Policy emphasizes various energy sources (Ministry of Power, 2022). Nevertheless, the lack of coordinated regional strategy and cross-border energy trade accords deter grid integration. Improved regional assistance is necessary to defeat policy disintegration and ensure resilient grid systems. Although technological innovations enhance every part of life, the nightmare of the smart grid is yet to be adopted, which is critical in improving grid resilience and organization of the intermittency of renewable energy sources. Martinot (2016) argues that integrating towards advanced energy storage can alleviate variation in renewable energy. South Asia has witnessed incremental adoption of these technologies, with India attracting the lead through initiatives like the National Smart Grid task (Ministry of Power, 2022). Despite this development, economies like Pakistan and Sri Lanka face technological breaches, prioritizing the need for awareness transfer and capacity-building to improve grid performance across the country.

Undeniably, renewable and nonrenewable electricity may enhance sustainable economic development and progress (Al-Mulali, 2014) chose eighteen American countries for the period of 1980 to 2010 by using DOLS estimation techniques. The results of the Pedroni cointegration test show that REC, NREC, GFCF, labor, and trade are cointegrated in the long run. Furthermore, the DOLS test outcome shows that all the variables have a favorable influence on GDP growth in the long run. The VEC Granger causality test conforms to feedback causality between the variables. Put into brief, the overall outcomes of the study reveal that REC is more significant than NREC in supporting economic growth in the selected countries both in the short run and long run. Based on the conclusion, this investigation recommends that the selected countries enhance their investment in sustainable energy such as wind, solar, and hydel. In addition, these countries must diminish their fossil fuel energy consumption by growing their energy effectiveness.

Recently, Lotze (2024) examined the incorporation of renewable energy into power systems, which needs advanced modeling to ensure efficiency and reliability in grid planning. This study examines a novel technique that couples energy system models with grid-planning models, increasing usual scenario-building processes by using an open-source energy model and regionalization method. It identifies grid overcrowding and expansion requirements, mainly for Europe's extra-high-voltage network. Results of the study show that a five-time increase in wind capability (844–970 GW) and a 17.9-times increase in photovoltaic (PV) capacity (2,147–2,571 GW) compared to 2020, besides a near-tripling of grid interconnection capability to 200 GW. These outcomes align with prior analysis, enhancing the level of infrastructure development required for renewable integration. Additionally, a successful energy evolution could decrease EU gas imports by 63.3% and oil imports by 83.5%, underscoring the economic and geopolitical earnings of renewable embracing. In contrast, Li B. et al., 2024) investigate China's energy transition with the global strive to fight climate change. This investigation recognizes the effects of key factors, including social-technology-economic, policy, governance, and investment. The unequal association was found by using the quantile-on-quantile regression (QQR) technique. Additionally, the synergic influences of key variables on China's energy evolution are observed in models 1 to 4. The results show that integration of the tradeoffs of falling coal emissions and promoting clean energy are vital for China's energy evolution. Moreover, urban growth, financial development, environmental taxes, environmental policies, and institutional superiority considerably maintain these efforts but show different synergistic effects. These results also strengthen the requirement for a more inclusive reaction to China's energy sustainability, especially harmonized policies and strategies in the coal-reliant industrial segment are significant for a victorious energy evolution.

Similarly, Li & Li (2022) assess the association between CO_2 emission and economic progress in the construction industry of China. The study uses panel data estimation for the 30 Chinese provinces during the 13th five-year development plan because it plays a vital role in sustainable energy transition. This era indicates a state of weak alignment, where economic growth still forces CO_2 emissions despite enhanced energy efficiency and decline efforts. The estimation uses the Tapio decoupling model and a spatial econometric model united with the STIRPAT framework; it shows that economic progress is in the increasing phase of the Carbon Dioxide Kuznets Curve (CKC) and demonstrates significant spatial spillover influence. While economic growth in one area can restrain emissions in neighboring areas, this influence is weaker than the direct emissions rising within the area. In addition, elements like employment and technological progress add to emissions, with spatial spillovers remaining low. The effect of these variables varies across provinces, highlighting the requirements for region-specific strategies to accomplish sustainable expansion in the construction sector. In contrast, Apergis et al. (2012) assess the influence of RE and NREC on economic growth in the case study of the USA. The study takes the Granger causality and error correction estimation method. The outcome of the panel cointegration test shows a long-run association between real GDP, RE, NRE, FCF, and labor force in the said country. The outcome reveals that, besides RE, the respective long-run coefficient evaluation is favorable and statistically significant. The results of the panel error correction method show unidirectional causality from renewable electricity to economic growth in the short run, but bidirectional causality observed in the long run. Moreover, the outcome also shows bidirectional causality between NRE and economic progress in both the long run and short run.

The empirical assessment of Kahia et al. (2017) evaluated the influence of both sources of energy and economic progress in the case study of 11 MENA Net Oil Importing Countries (NOICs) for the data period 1980–2012. The study uses a multivariate panel estimation technique to estimate the long-run association between the variables. Additionally, a panel of Granger causality tests is used to estimate the causal relationship among variables. The outcomes of the empirical analysis show the long-term association between GDP, RE, NRE, GFCF, and labor force in the selected countries. The empirical endings from the panel Error Correction Model observe bidirectional causality between RE and economic development and between NRE and economic growth. Furthermore, our experiential results offer proof for a two-way (bidirectional) causal relationship in both the long run and short run. In fact, RE and NRE confirm the substitutability and interdependence between these two sorts of energy sources.

Put into brief; the cited literature reveals that economic factors, technical factors, and policy factors play a vital role in reshaping grid resilience and modernization. Indeed, these studies particularly focused on developed countries and regions and ignored underdeveloped regions such as South Asia's countries. Now this study aims to bridge this vital gap and investigate the grid resilience and grid transition by analyzing economic, technical, and policy factors.

Materials and Techniques

This chapter includes an estimation strategy by examining the synergy of economic technical, and policy factors in renewable integration in the selected South Asian economies. The study used a quantitative data analysis by using FMOLS and DOLS.

Data and Sources

The present study aims to analyze grid resilience and green transformation by investigating the synergy of economic, technical, and policy features in grid resilience in the selected South Asian countries, namely India, Bangladesh, Pakistan, Nepal, and Sri Lanka. The data for this analysis was sourced from various reputable organizations for the period of 2000 to 2023. Hence, sources of data, status of variables, and scales are given below.

Justification of Variables

Grid Resilience (Electricity Distribution Losses): This variable is used as a proxy for grid resilience. It shows technical inefficiencies or obsolete infrastructure caused by electricity distribution loss. The study measures in ratio scale in amount (electricity lost in billions of kilowatt-hours). The lower distribution losses depicted a more resilient and efficient grid and vice versa. It is crucial for sustaining renewable energy integration and guaranteeing grid stability. This variable is sourced from the Energy Information Administration (EIA).

The five independent variables are distributed in three sections such as technical factors, economic factors, and policy factors which are given below.

Technical Factors

Capacity Of Renewable Energy: The capacity of renewable energy shows the total installed capacity of renewable energy sources measured in megawatts (MW). This variable represents a country's ability to generate electricity from green and sustainable sources. This data is sourced from IRENA.

Carbon intensity (CO_2 Emission): The variable carbon intensity measures the natural logarithm of carbon emissions per unit of GDP and regulates purchasing power parity (PPP). It shows how an economy efficiently generates economic output while diminishing carbon emissions. This variable is crucial for investigating the separation of the effect of economic growth from carbon emissions by examining the RE policies and green transition. This variable is sourced from WDI.

Economic Factors

Investment in Renewable Energy: Investment in renewable energy, as a variable, shows the financial resources allotted to renewable energy projects such as solar and wind electricity production. It serves as an independent variable to examine impacts on grid resilience. It is measured at $ million. The data is sourced from IRENA.

Access to Electricity: The variable access to electricity percentage of the total population measures how many people have the facility electricity. This variable is a crucial indicator of infrastructure growth and economic development. It includes the access of households, businesses, and public services to the electricity facilities. A higher proportion shows greater electricity access, which is necessary for fostering industrialization, improving living standards, and supporting economic activities. This variable is sourced from WDI.

Country Policy and Institutional Assessment (CPIA): The CPIA Rating (1 to 6) is an ordinal variable organized by the World Bank. It estimates the quality of policies and institutional support for the environmental sustainability of a country. It considers pollution control, biodiversity safety, and climate change. The higher ratio shows stronger policy frameworks and vice versa. The scale ranges from 1 (very weak policies and institutions) to 6 very strong policies and institutions. The data is sourced from WDI database.

Econometrics Methodology

To examine the determinants of grid resilience, we create an econometric model that estimates the impact of key economic, technical, and policy factors on renewable energy integration. The model is precise as follows: as in Eq... (1):

$$GR_{it} = \beta_0 + \beta_1 IRE_{it} + \beta_2 AE_{it} + \beta_3 CRE_{it} + \beta_4 CO_{2it} + \beta_5 CPIA_{it} + \varepsilon_{it}$$

The equation is divided into three parts, economic factors, technical factors, and policy factors in order to examine multidimensional influence on grid resilience in various entities (i) over time (t). in the model, economic factors include, Investment in Renewable Electricity (IRE) and Access to Electricity (AE). Technical factors include Capacity of Renewable Energy (CRE) and Carbon Emission intensity (CO_2), while policy factors include Policy and Institutions for Environmental Sustainability Rating (CPIA). The module also consists of intercept (as the constant term and indicates the coefficients that assess the impact of each independent variable. The error term ε accounts for unobserved factors affecting grid resilience and sustainability.

Estimation Strategy

Foundation of Model: In panel data analysis, before choosing any appropriate statistical estimation techniques, we go through various necessary steps. Initially, the study employs several pre-estimation diagnostic tests to choose a suitable estimation method. That's why it initially conducts descriptive statistics to check for outliers and divergence in data. Secondly, CD (Breusch & Pagan, 1980) is to check for cross-section dependency. Furthermore, to check stationarity in variables, the study applied IPS and LLC unit-root tests. Next, for the long relationship among the variables, we need a cointegration test; the study applied the Koa cointegration test in order to measure the long-term nexus among the variables. When it confirms that a long-run relationship exists, the next laborious step is to determine which model would be appropriate. For this purpose, various econometrics tests are used, such as the Durbin-Watson test (1996) to check autocorrelation and the Durbin-Wu-Hausman test of Durbin and Hausman (1990) to assess endogeneity. On the basis of these tests, the study decided to amply FMOLS and DOLS estimation methods (Pedroni, 1996) for estimating long-run association. However, FMOLS and DOLS are estimation methods used for co-integration. However, FMOLS measures serial correlation and endogeneity, while the DOLS corrects for endogenous regressors and lags of the independent variables. Moreover, FMOLS can't assess causal links between variables; therefore, in the next step, we applied the causality test (Dumitrescu & Hurlin, 2012) to check the direction of causality among all variables. Hence, assumptions, limitations, advantages, and interpretation of the said techniques are discussed given below.

Diagnostic Tests

Cross Section Dependency Test (CD): CD means a situation in which observations in a dataset are not independent of each other across different cross-sections. It can lead to inefficient guesses and invalid inferences if not measured. Hence, to check cross-sectional interdependence, the study applied the Breusch and Pagan (1980) LM and Pesaran (2004) CD test. In both tests, the null hypothesis is no cross-sectional interdependence.

$$CD = \frac{\sqrt{T(T-1)}}{2} . \frac{1}{N} \sum_{i \neq j} \rho_{ij}$$

T represent, time dimension, N shows cross sectional dimensions and ρ refers to the correlation coefficient between residuals of cross-sectional unit i and j. Moreover, $\sum i \neq j$ shows summation overall unique pairs of cross-sectional units.

Kao Cointegration Test: The Kao Cointegration Test is used to measure the long-term equilibrium association between variables in panel data. If the residuals are stationary, a cointegrating relationship among variables is recommended. The test is based on an error correction model. The null hypothesis is that there is no cointegration.

$$Y_{it} = \alpha_i + \beta X_{it} + \gamma Y_{it-1} + \delta X_{it-1} + \mu_{it}$$

Y is used for the dependent variable, X is the independent variable, $\propto$ it is constant, and $\boldsymbol{\beta}$ refers to the coefficient. Additionally, $\boldsymbol{\gamma}$ refers coefficient of the lagged dependent variable.

Panel Unit-Root Tests: A unit root is an issue in panel data when the mean and variance are not constant over time, frequently due to individual-specific heterogeneity and autocorrelation. Heterogeneity arises from differences across entities (e.g., countries, companies, etc.), while serial correlation reflects dependence on past values. To test for stationarity, this study utilizes second-generation panel unit-root tests, particularly LPS and LLC.

LPS $\mathbf{y_{it}} = \propto_i + \boldsymbol{\beta}_{\mathbf{iyit-1}} + \boldsymbol{\mu}_\mathbf{t} + \boldsymbol{\epsilon}_{\mathbf{it}}$

LLC $\mathbf{y_{it}} = \propto_i + \boldsymbol{\beta}_{\mathbf{yit-1}} + \boldsymbol{\mu}_\mathbf{t} + \boldsymbol{\epsilon}_{\mathbf{it}}$

The above equation shows that LPS focuses on large cross sections and heterogeneity, while LLC is for smaller panel data sets and homogeneity.

Durbin-Watson Autocorrelation Test: The DW test is employed to check serial correlation within the regression's error term. A serial correlation exists when the residuals of a regression model are interrelated. To perform the DW test interpretation, see below:

$$\mathbf{DW} = \sum\nolimits_{\mathbf{t=2}}^{\mathbf{T}} (\mathbf{et} - \mathbf{et} - \mathbf{1})^2 \,/ \sum\nolimits_{\mathbf{t=1}}^{\mathbf{T}} \mathbf{e_t^2}$$

Where T refers to a number of observations, it shows the error term, $\sum_{\mathbf{and\ t=2}}^{\mathbf{T}} \mathbf{et} - \mathbf{et} - \mathbf{1}$) shows the sum of squared differences between residuals.

Variance Inflation Factor (VIF): The VIF is a statistical method used to measure multicollinearity in the regression model. It exists when two or more variables in a model are greatly correlated. It can make the estimation of the coefficient unreliable.

$$\mathbf{VIF_j} = \frac{\mathbf{1}}{\mathbf{1 - R_j^2}}$$

This formula helps the examinee with multicollinearity, while the R^2 shows the proportion of variance.

Durbin-Wu-Hausman Endogeneity Test: The Durbin-Wu-Hausman (DWH) test is a statistical method used to estimate endogeneity issues in a regression model. Endogeneity means the existence of a relationship between the regressor and the residual of a regression model. When endogeneity exists in data, the long-run estimation gives unbiased estimates.

Dumitrescu-Hurlin Panel Causality Test (DHPCT): Causality investigation is crucial in econometrics and panel data estimation because it assists in determining the direction and nature of associations among variables. With the FMOLS model, the DHPCT is a crucial choice for evaluating causality. This test is appropriate for heterogeneous panel data and helpful for cross-sectional dependence and heterogeneity between entities.

Long Run Estimation Techniques: The study comprehensively conducted all the above tests; hence it concludes that the most suitable estimation techniques are FMOLS and DOLS. Indeed, FMOLS an a econometric method used to measure long-run relationships between variables. It is useful to adjust issues like endogeneity and serial correlation to offer a consistent and efficient investigation of the long-term equilibrium between variables. These techniques are not only useful in estimating small sample sizes but are also capable of taking into account serial autocorrelation and endogeneity issues (Phillips & Hansen, 1990). Following Adom & Kwakwa (2014), the equation expresses the FMOLS estimator for the model in equation (1) as given below.

$$\mathbf{Y_{it}} = \propto_i + \boldsymbol{\beta}\mathbf{x_{it}} + \boldsymbol{\mu}_{\mathbf{it}}$$

The equation () shows, $\mathbf{Y_{it}}$ is independent variable for unit i at time t, while $\mathbf{X_{it}}$ in dependent variable, $\propto_i$ individual fixed effects, $\boldsymbol{\beta}$ long run parameter of interest and $\boldsymbol{\mu}_{\mathbf{it}}$is error term in the model.

For reliability, the study also used the DOLS (Stock & Watson, 1993) method. For the robustness of FMOLS findings, especially in its design to measure the issue of addressing endogeneity and serial correlation lags of the independent variables in the model, the DOLS estimator for the model in equation (1) is specified in equation () as follows:

$$\mathbf{Y_{it}} = \propto_i + \boldsymbol{\beta}\mathbf{x_{it}} + \boldsymbol{\mu}_{\mathbf{t}} \sum_{\mathbf{k=-q}}^{\mathbf{q}} \boldsymbol{\gamma}\mathbf{j}\Delta\mathbf{xi}, \mathbf{t} - \mathbf{j} + \boldsymbol{\mu}_{\mathbf{it}}$$

Y_{it} is a dependent varaible, while $\propto_i$ is intercept or fixed effect in the model. $\beta x_{it}$is independent var**iable**, and $\Delta xi, t - j$ leads and lags of the first differences of x_{it}. Moreover,$\gamma_j$is coefficent for the leads and loags and lastly the μ_{it} is error term.

After authenticating the cited statistical techniques, we reached the decision that FMOLS and DOLS estimation techniques are appropriate to estimate the long-run effect of economic, technical, and policy factors on grid resilience in the selected South Asian countries. In a nutshell, this methodology chapter presents a planned approach to examine the synergy of economic, technical, and policy factors in renewable energy addition, backed by emerging diagnostic tests, allowing for accurate assessment of long-run associations and providing insights into how these factors collectively develop grid resilience in the selected South Asian countries.

Results and Discussion

Results

This section of the study represents the results of the empirical analysis of each test separately. Table 1 depicts descriptive statistics of the data set. Initially, the mean value of 2.033 shows the effects of grid resilience (distribution losses) on average, with a maximum value of 5.694, showing that a few countries, like Pakistan and India, have huge electricity distribution losses. Meanwhile, the minimum value of -0.916 indicates low electricity distribution losses, such as in Bhutan and Sri Lanka. The mean value of 1.617 indicates the scale of investment in renewable energy, 3.299 shows renewable energy capacity, 1.172 shows the quality of institutions and policies, 4.536 shows access to electricity, and -0.795 shows the intensity of CO_2 emissions in each country. The maximum and minimum values show the respective results of each variable with respect to the mentioned country. The value of standard deviations shows varying levels of data dispersion. The low p-value shows a significant relationship among the variables and vice versa. Lastly, the dataset contains 120 reliable observations for each variable, ensuring consistency for further investigation. Similarly, table 2 exposes the correlation matrix that grid resilience (electricity distribution loss) is positively correlated with CO_2 emissions, representing that higher distribution losses align with increases in CO_2 emissions.

Table 1

Descriptive Statistic

Mean	Maximum	Minimum	Std. Dev.	Prob.	Obs
2.033	5.693	-0.916	2.019	0.004	120
1.617	6.835	-4.605	2.893	0.162	120
3.300	4.586	0.952	1.101	0.000	120
1.172	1.386	0.916	0.129	0.191	120
4.536	4.610	4.324	0.065	0.000	120
-0.796	0.218	-1.804	0.568	0.050	120

Additionally, it has a positive association with investment in renewable energy, renewable energy capacity, and electricity access but an adverse relation with country policy and institutional assessment. Additionally, the CD test shows the outcome of the Cross-Sectional Dependency (CD) test. The Pesaran scaled LM with a probability value of 0.1289, demonstrating no significant cross-sectional dependence at the 5% significance level. The bias-corrected scaled LM with a probability value of 0.1586 additionally supports the absence of significant CD. The Pesaran CD has a probability value of 0.6421, which also proposes that cross-sectional dependence does not exist in the data. Overall, these three results represent that there is no cross-sectional dependency in the dataset. Moreover, the next results in Table 3 indicate the outcomes of VIF, with the minimum value of 1.0,1 for GR representing low multicollinearity, followed by 1.22 for RE and 1.22 for RE capacity. CO_2 has a maximum value of 1.44, followed by CPIA 1.318, but it remains below the threshold. Overall, the VIF result suggests that there is no multicollinearity in the model. Similarly, table 5.1 shows the results from the IM, Pesaran, and Shin (IPS) test, indicating varying results for all the variables. Specifically, ln Inv RE with p-vap-value 0.0002 is stationary at level, but all other variables are stationary at first difference. While the results of the Levin, Lin, and Chu test are mixed and the same as the previous test, ln Inv RE is significant at level, and all other variables are stationary at the first difference.

Table 2

Correlation Matrix

	GR DIS LOSS	ln INV RE	ln CPIA	ln RE CAP	ln Electricity	ln CO_2
GR DIS LOS	1					
lnRE	0.428	1				
ln CPIA	-0.261	-0.119	1			
ln RE CAP	0.430	0.261	0.262	1		
ln Electricity	0.301	0.092	0.321	0.153	1	
ln CO_2	0.925	0.417	-0.209	0.453	0.182	1

Table 3

Results of the Cross-Sectional Dependency Test

Test	Statistic	Prob.
Pesaran scaled LM	1.518631	0.1289
Bias-corrected scaled LM	1.409936	0.1586
Pesaran CD	0.464772	0.6421

Table 4

Results of VIF

Variable	Variance	VIF
GR DIS LOS	9.19E-05	1.061307
ln Inv RE	0.070210	1.229987
ln CPIA	0.053348	1.318071
ln RE CAP	0.252328	1.218589
ln Electricity	0.015302	1.137980
ln CO_2	0.153848	1.447940

Table 5

Results of Panel Unit-Root Tests

		Level		1st Difference	
Tests	Variables	Statistics	Prob.	Statistics	Prob.
Levin-Lin-Chu	GR Dis Loss	-0.61872	0.2681	-2.3430	0.0096
	ln Inv RE	-3.2427	0.0006	-7.4522	0.0000
	ln CPIA	-0.5499	0.2912	-3.6457	0.0001
	ln RE cap	-0.2330	0.4079	-5.3587	0.0000
	ln Electricity	-1.2805	0.1002	-9.6311	0.0000
	ln CO_2	1.1799	0.8810	-2.6329	0.0042

Tests	Variables	Level Statistics	Prob.	1st Difference Statistics	Prob.
Im-Pesaran-Shin	GR Dis Loss	-0.61872	0.2681	-2.3430	0.0096
	ln Inv RE	-3.2427	0.0006	-7.4522	0.0000
	ln CPIA	-0.5499	0.2912	-3.6457	0.0001
	ln RE cap	-0.2330	0.4079	-5.3587	0.0000
	ln Electricity	-1.2805	0.1002	-9.6311	0.0000
	ln CO_2	1.1799	0.8810	-2.6329	0.0042

Moreover, the results of the Kao cointegration test reveal that the probability value of 0.0106 is less than the 5% level of significance, so the study rejects the null hypothesis of no cointegration. This recommends that there is a long-run relationship among the variables despite any short-term deviations. The residual variance and HAC variance are also significant, which shows that the model fits the data practically well.

Table 6

Results of Kao Co-integration test

Metric	Value
Null Hypothesis	No co-integration
ADF t-Statistics	-2.302980
Residual Variance	0.0106
HAC Variance	0.010701
Prob.	0.0106

Table 7

Results of Long-run Estimates (FMOLS & DOLS)

	Variable	Coefficient	Std. Error	t-Statistic	Prob.
FMOLS	GR (Dis Loss)	-0.387118	0.068805	-5.626289	0.0000
	ln Inv RE	-2.570028	0.960923	-2.674541	0.0233
	ln CPIA	-0.318465	0.051938	-6.131664	0.0000
	ln RE cap				
	ln Electricity	0.849294	0.328734	2.583533	0.0160
	lnCO_2				
DOLS	GR (Dis Loss)	-0.480449	0.126999	-3.783087	0.0003
	ln Inv RE	-1.355039	0.495476	-2.734824	0.0128
	ln CPIA	-0.179611	0.000636	-282.3016	0.0000
	ln RE cap				
	ln Electricity	1.989006	0.468003	4.249985	0.0001
	lnCO_2				

Table 7 shows and compares results of FMOLS and DOLS in the long run. It empirically investigates the impact of renewable energy investment, renewable energy capacity, access to electricity, and institutional quality on grid resilience (distribution loss) in the selected South Asian countries.

Indeed, both techniques, FMOLS and DOLS, give the same sign of relationship among the variables, but their sensitivity in coefficients is different, such as investment in renewable energy, CPIA, and capacity of renewable energy having negative and significant effects on grid resilience, but their coefficient values are varying. This indicates that an increase in investment in renewable energy improves the quality of the Country Policy and Institutional Assessment (CPIA), and an increase in renewable energy capacity may decrease electricity and distribution loss. Consequently, it leads to enhanced grid resilience and sustainability of electricity interruption. Additionally, access to electricity and CO_2 emissions have a positive and significant influence on grid resilience, but their coefficient values in FMOLS and DOLS are varying. Hence, it reveals that an increase in access to electricity and CO_2 emission decline grid resilience and sustainability in the selected South Asian countries.

Indeed, comparisons between the FMOLS and DOLS provide reliable results, representing that all variables have a statistically significant influence on grid resilience in the long run. However, the coefficients of some variables differ between the two techniques. Despite these differences, the overall outcomes support the importance of renewable energy, carbon intensity, and electricity access, which play a crucial role in the shaping of grid resilience and sustainability.

Table 9

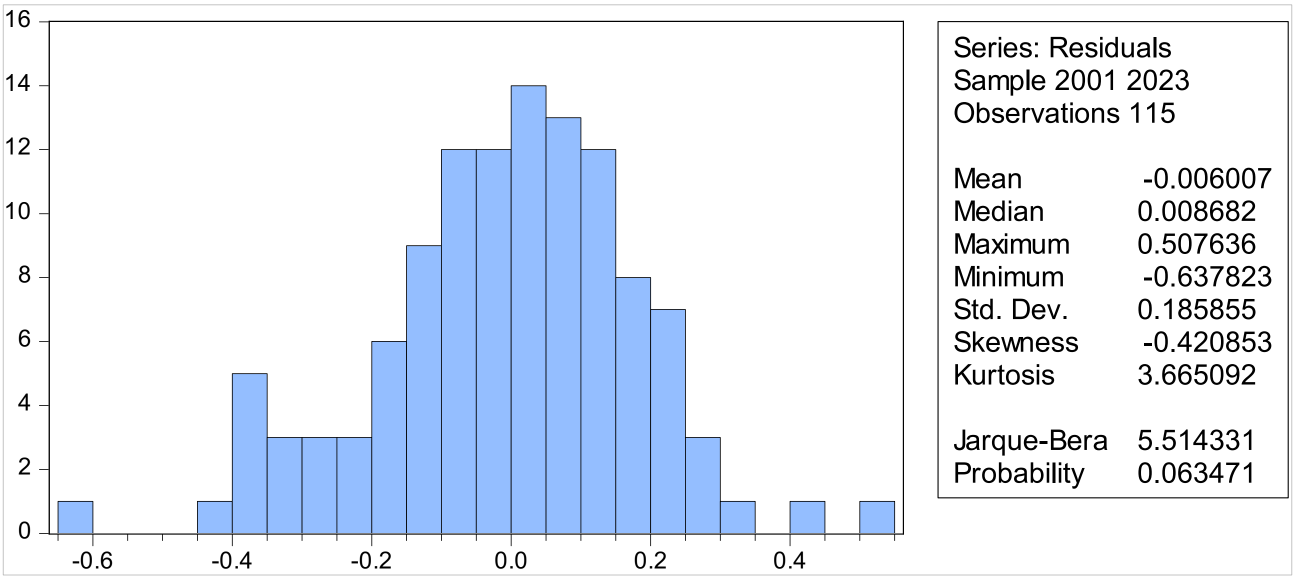
Results of Serial Correlation Test

Durbin-Watson stat	0.245174

The Durbin-Watson value is 0.245174, which is less than 2, which shows the presence of a positive serial correlation in the model. As values closer to 0 indicate a strong autocorrelation in the model. This shows the model's errors are correlated over time. Moreover, normality in data is also crucial while investigating a series. Now the study analyzes the histogram test for the normality.

Figure 1

Results of the Histogram Normality Test



The value of the Jarque-Bera test is 5.51 with a p-value of 0.06, which shows that the data set is normally distributed at the 5% level of significance. Therefore, the study concludes that the data is normally distributed. Additionally, the issue of causality in the data set has a vital importance among the variables. Now this study investigates the causality with the Dumitrescu Hurlin Panel Causality Tests.

Table 10

Results of Dumitrescu Hurlin Panel Causality Tests

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
Investment in RE does not homogeneously cause grid resilience	3.567	1.12211	0.2618
CO_2 emission does not homogeneously cause investment in RE	3.474	1.04222	0.2973
LN_RE_CAP does not homogeneously cause grid resilience	7.096	4.16649	3.E-05
Grid resilience does not homogeneously cause institutional quality	1.792	-0.466	0.68
LN_CPIA does not homogeneously cause grid resilience	2.427	0.135	0.88
Grid resilience does not homogeneously cause institutional quality	2.224	-0.036	0.97
Access to Electricity does not homogeneously cause grid resilience	3.556	1.116	0.26
grid resilience does not homogeneously cause Access to Electricity	4.135	1.612	0.10
CO_2 emission does not homogeneously cause grid resilience	4.374	1.819	0.06
Grid resilience does not homogeneously cause CO_2 emission	3.723	1.256	0.20

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
LN_RE_CAP does not homogeneously cause investment in renewable energy	1.775	-0.478	0.67
Investment in Renewable energy does not homogeneously cause REC	0.642	-1.405	0.16
LN_CPIA does not homogeneously cause Investment in RE	5.373	2.044	0.007
Investment in RE does not homogeneously cause LN_CPIA	5.249	2.518	0.010
Access to Electricity does not homogeneously cause Investment in RE	4.371	1.807	0.06
Investment in RE does not homogeneously cause Access to Electricity	0.865	-1.274	0.22
CO_2 emission does not homogeneously cause Investment in RE	1.809	-0.339	0.69
Investment in RE does not homogeneously cause CO_2 emission	2.405	0.119	0.90
LN_CPIA does not homogeneously cause LN_RE_CAP	2.649	0.383	0.74
LN_RE_CAP does not homogeneously cause LN_CPIA	1.383	-0.766	0.44
Access to Electricity does not homogeneously cause LN_RE_CAP	2.066	-0.126	0.86
LN_RE_CAP does not homogeneously cause Access to Electricity	1.591	-0.582	0.56
CO_2 emission does not homogeneously cause LN_RE_CAP	11.374	7.660	4.65
LN_RE_CAP does not homogeneously cause CO_2 emission	5.076	2.422	0.0153
Access to Electricity does not homogeneously cause LN_CPIA	4.515	1.916	0.0524
LN_CPIA does not homogeneously cause Access to Electricity	4.190	1.656	0.0970
CO_2 emission does not homogeneously cause LN_CPIA	1.599	-0.575	0.56
LN_CPIA does not homogeneously cause CO_2 emission	3.409	0.985	0.32
CO_2 emission does not homogeneously cause Access to Electricity	1.934	-0.286	0.77
Access to Electricity does not homogeneously cause CO_2 emission	5.542	2.826	0.004

In fact, causality means the directional impact of variables among each other; it may be bi-directional, uni-directional, or have no impact. The Dumitrescu Hurlin Panel Causality Tests show significant bidirectional causality between renewable energy investments and CPIA and between carbon intensity and renewable energy capacity. Moreover, renewable energy capacity also considerably causes grid resilience, while access to electricity impacts carbon intensity. However, no major causality exists among grid resilience, renewable energy investment, CPIA, and electricity access in South Asian countries.

Conclusion and Recommendations

This analysis examines the synergy of technical, economic, and policy factors on grid resilience in selected South Asian countries consisting of India, Nepal, Pakistan, Bangladesh, and Sri Lanka over the period 2000–2023. The empirical investigation employs two robust econometric methods, Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS), to evaluate the long-run association between grid resilience and its determinants. The results provide key insight into the multidimensional factors shaping grid resilience and the sustainability of electricity distribution. The Kao cointegration test shows a significant long-run association among the variables, indicating that technical, economic, and policy factors are interrelated and jointly influence grid resilience over time. Both statistical methods, FMOLS and DOLS, validate the statistical significance of the explanatory variables, though with differences in coefficient sensitivity.

Key Findings

Similarly, as the aim of the study, the findings also consist of three parts.

Economic Factors

Investment in Renewable Energy (IRE): The empirical results reveal a negative and significant influence on grid resilience, suggesting that increased investment in renewable energy electricity decreases electricity distribution losses, consequently enhancing grid resilience and the sustainability of a smooth electricity supply.

Technical Factors

Capacity of Renewable Energy (CRE): The outcomes of empirical investigation show a negative and significant effect on grid resilience. It reveals that an increase in renewable energy capacity may decline electricity distribution losses and fortify grid resilience and sustainability.

Carbon Emission Intensity (CO_2): Positively and significantly affects grid resilience, suggesting that higher emissions correlate with reduced grid efficiency and sustainability.

Policy Factors

Country Policy and Institutional Assessment (CPIA): The empirical results of CPIA show a negative and significant effect on grid resilience, highlighting the vital role of hefty environmental policies and institutional quality in falling distribution losses and improving grid reliability.

Recommendations

The study highlights the significance of targeted technical, economic, and policy interventions to improve grid resilience and ensure sustainable electricity distribution:

Economic Priorities: The authorities and policymakers should prioritize and focus on strategically enhancing investments in renewable energy infrastructure to minimize distribution losses while improving grid reliability.

Technical Advancements: Increasing renewable energy capacity is necessary to lessen dependence on traditional energy sources (coal, oil, gas), thereby declining emissions and improving grid efficiency.

Policy and Institutional Reforms: Policy formulation and strengthening of institutional frameworks are chiefly crucial for every country, especially for the underdeveloped countries, thereby reducing vulnerabilities and enhancing long-term energy sustainability.

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