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Renewable Energy, Green Finance, Ecological Footprints and Environmental Quality: A New Insights from South Asian Countries

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ABSTRACT

Within the context of South Asian nations, this study investigates how factors such as FDI, ecological footprint, green finance, utilization of renewable energy sources, and Information and Communication Technology all have a role in determining the quality of the environment. In order to investigate the dynamic interrelationships that exist among these elements, this study makes use of panel data and in order to evaluate the nature of the connection that exists between the variables that are the subject of this investigation, the research performs slope homogeneity tests as well as cross-sectional dependency tests. The research indicates that the ecological footprint, green financing, FDI, use of renewable energy, and ICT are all collectively responsible for the increase in carbon emissions and the deterioration of environmental conditions. However, the use of renewable energy sources has been shown to have an effect that is inversely proportional to the release of carbon emissions. The study utilizes a mixed order of integration (0,1) in order to derive short-run and long-run correlations among South Asian countries. The results indicate that several factors are exerting an influence on the quality of the environment. However, it is seen that the consumption of renewable energy is having an inverse impact on carbon emissions.

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1. Introduction

The economics of South Asian countries including India, Pakistan, Nepal, and Sri Lanka, as well as Bangladesh, are the secondary subject of this research. These economies are now enjoying tremendous economic development, with India having the most developed economy. India's economy is now the top user of energy in South Asia. This is because the greater economic growth in the area needs more energy consumption. According to Depren, Kartal, Çelikdemir, and Depren (2022); Raheem, Tiwari, and Balsalobre-Lorente (2020); Umair and Yousuf (2023) the economies of South Asia usually depend on conventional fossil fuels for economic growth, which poses a danger to the quality of the environment in the area. Mughal et al. (2022) state that in spite of the economic success, these nations have not done particularly well in terms of maintaining a sustainable environment. A positive relationship between ecological footprints and carbon emissions is plausible and can be observed in some contexts Xu et al. (2022), although the relationship can vary depending on several factors. The ecological footprint measures the environmental impact of human activities in terms of the resources consumed and waste produced, expressed in terms of global hectares (Gha). It considers various components, including carbon emissions, to assess how much biologically productive land and sea area are needed to support a particular lifestyle or level of consumption (Asif et al., 2023;

Murshed et al., 2022). Regions or countries with high levels of consumption, characterized by large ecological footprints, are often associated with higher carbon emissions. This is because increased consumption often leads to more energy use, transportation, and industrial activities, all of which can result in higher carbon emissions.

Renewable energy and environmental quality are two topics that are closely related to one another and have recently attracted a significant amount of attention from people all over the world as a direct result of rising concerns regarding climate change and the deterioration of the environment. One of the most major benefits provided by renewable energy sources such as solar, wind, and hydropower is that these sorts of sources produce relatively low amounts of greenhouse gas emissions. According to Ali, Rehman, Rehman, and Ntim (2022), when fossil fuels like coal, oil, and natural gas are burned for energy, they produce emissions of carbon dioxide as well as other types of pollution. In contrast, the creation of power from renewable sources produces very little to almost no direct emissions. The transition to renewable energy contributes to an improvement in air quality by lowering emissions of hazardous air pollutants, such as Sulphur dioxide and particulate matter are responsible for illnesses that are linked to air pollution and causing a negative impact on health of humans and ecosystems. By displacing fossil fuel-based power generation, renewable energy sources help mitigate climate change. The reduction in CO_2 emissions from the energy sector contributes to limiting global warming and its associated impacts. Many conventional power plants, particularly coal and nuclear facilities, require significant amounts of water for cooling purposes. Renewable energy technologies generally have lower water consumption, reducing stress on local water resources, especially in regions facing water scarcity. Renewable energy projects can be designed to minimize their impact on local ecosystems and biodiversity (Caglar, Guloglu, & Gedikli, 2022). Careful site selection, habitat restoration, and bird- and bat-friendly turbine designs in wind energy projects are examples of efforts to protect wildlife and ecosystems. Renewable energy technologies like wind turbines and solar panels typically produce less noise pollution compared to some conventional power plants, which can help maintain peaceful and healthy living environments for nearby communities.

In the framework of efforts to combat climate change and promote sustainability, it is anticipated and desired that there would be a negative link between green money and carbon emissions. According to Jiakui, Abbas, Najam, Liu, and Abbas (2023), the term green finance refers to financial products and services that back initiatives that are favourable to the environment and sustainable. The following is a list of the primary reasons why it is desirable to have a negative link between green finance and carbon emissions: Green funding is typically redirected towards the development of clean and renewable energy projects including wind, solar, hydro, and geothermal power. In contrast to energy sources that rely on fossil fuels, these initiatives provide electricity without releasing any carbon dioxide into the atmosphere. Green finance is a sort of financing that can be used to help support energy efficiency projects in a range of businesses and sectors, such as manufacturing, building, and transportation, amongst others. This type of financing is also known as sustainable finance. The adoption of practises and technologies that are more energy efficient leads to a reduction in overall energy consumption, which in turn results in a lessening in the amount of carbon emissions. The usage of energy and the pollutants that come with it can be cut down by finding financing for green building projects and upgrading existing structures for energy efficiency. This includes heating, cooling, and lighting. Carbon offsetting programs, such as reforestation and afforestation, are supported by some green finance initiatives. These projects remove carbon dioxide from the environment by planting trees, which effectively offsets emissions from other sources. Green finance encourages businesses and industries to adhere to sustainability standards and practices that prioritize reducing environmental impacts, including carbon emissions.

2. Literature Review

This section studies the existing body of literature that investigates the association between economic growth, ecological footprints, utilisation of renewable energy, revenue from natural resources, green finance, ICT, and the impact that these factors have on the environment. Specifically, the section focuses on the use of renewable energy. In the field of environmental research, the relationship between the utilization of renewable energy sources (RES) and environmental footprints (EFP) has acquired substantial prominence. It is claimed that RES can help to policy regarding the environment and energy security. By implementing

RES into manufacturing and production processes, industries want to improve their efficiency and profitability while simultaneously decreasing their waste (Dogan, Madaleno, & Taskin, 2021). This will result in a decrease in EFP. According to the empirical results of Agbede, Bani, Azman-Saini, and Naseem (2021), RES plays an important part in environmental governance and has an effect on environmental contamination. Suki et al. (2022) carried out their research in Malaysia. These locations included both developed and developing nations. They carried out panel co-integration tests using a dataset that contains 6 countries from 1995 to 2022, which spans the years 1995 to 2022. On the other hand, countries that have high incomes have a connection between RES and carbon emissions that goes in the opposite way. Another research that was carried out by Murshed, Ahmed, Kumpamool, Bassim, and Elheddad (2021) focuses on the influence that RES has on the ecological footprint of Small and Sustaining Economies (SSE). According to the research, RES helped to lessen the ecological impact that these locations leave behind. In a similar vein, substantial study that was carried out in a variety of nations by Akinsola et al. (2022) shows evidence that RES lowers EFP levels. Environmental policy and research have begun to devote a substantial amount of attention to green finance and the role it plays in ensuring ecological sustainability. According to Nawaz et al. (2021), green finance refers to the practise of making financial investments with the intention of fostering sustainability initiatives and practises that uphold environmental integrity. Green financing serves to prevent environmental deterioration and increase environmental quality (Q.-J. Wang, Wang, & Chang, 2022). This is accomplished by encouraging large-scale investments in cutting-edge technology, such as breakthroughs that do not rely on fossil fuels. However, the relationship between environmentally friendly finance and ecological footprint (EFP) is a topic that is still being researched. Afshan, Yaqoob, Meo, and Hamid (2023); Dai, Alvarado, Ali, Ahmed, and Meo (2023) conducted research to determine the impact that green finance has on the preservation of the natural environment in the top ten nations that invest in green finance.

In recent decades, the information and communications technology sector has grown increasingly competitive as a direct result of the dramatic rise in the amount of data used by individuals, organisations, and governments (Nathaniel, Yalçiner, & Bekun, 2021; Ofori & Asongu, 2021). This is a direct result of the remarkable rise in the amount of data used by individuals, organisations, and governments (Nathaniel et al., 2021). According to (Haseeb et al., 2019), information and communications technology may help reduce environmental pollution in two different ways. First, it may encourage the use of renewable energy and energy-efficient practises. Second, it may lower emissions from other sectors of the economy. The study that has been done on the link between information and communications technology (ICT) and environmental footprint (EFP), on the other hand, has yielded inconsistent results. The findings of a number of research indicate that information and communications technology (ICT) requires a significant amount of energy, which contributes to higher EFP levels. There is a connection between information and communications technology (ICT) and environmental contamination in a number of locations, according to research that was carried out by Dogan et al. (2021); (Raheem et al., 2020), amongst others.

3. Data and Methodology

The estimation of panel data variables, including as the environment, and ecological footprints, is a key concern for economists in the current decade because there are so many econometric issues to take into account when collecting data and analyzing the results. This section will discuss a number of steps connected to Panel Data and the selection of a suitable estimation approach.

3.1. Data Sources, Research Model and Methodology Data

This research analyses the dynamic connections between ecological footprint (EF), green financing (GF), FDI, and renewable energy (REEC). The authors obtained data on South Asian nations for the variables of interest for the period of time spanning 1995-2022 from two distinct data sources. The information about ecological footprint is obtained from the Global Footprint Network, while the information regarding CE, FDI, REEC, GF, and ICT is taken from the World Development Indicator.

3.2. Specification of Econometric Models

In this study one Dependent model are formulated with Carbon emission and some supporting variables. The supporting variables are FDI, Ecological Footprints, Renewable energy, Green Finance and ICT. The functional form of the model is shown below:

$$Corbon\ emission(CE) = f(\mathrm{EF, GF, FDI, REEC, ICT})$$

$$Corbon\ Emission = f(Ecological\ Footprints, Green\ Finanace, Foriegn\ direct\ investment, Renewable\ Energy, ICT)$$

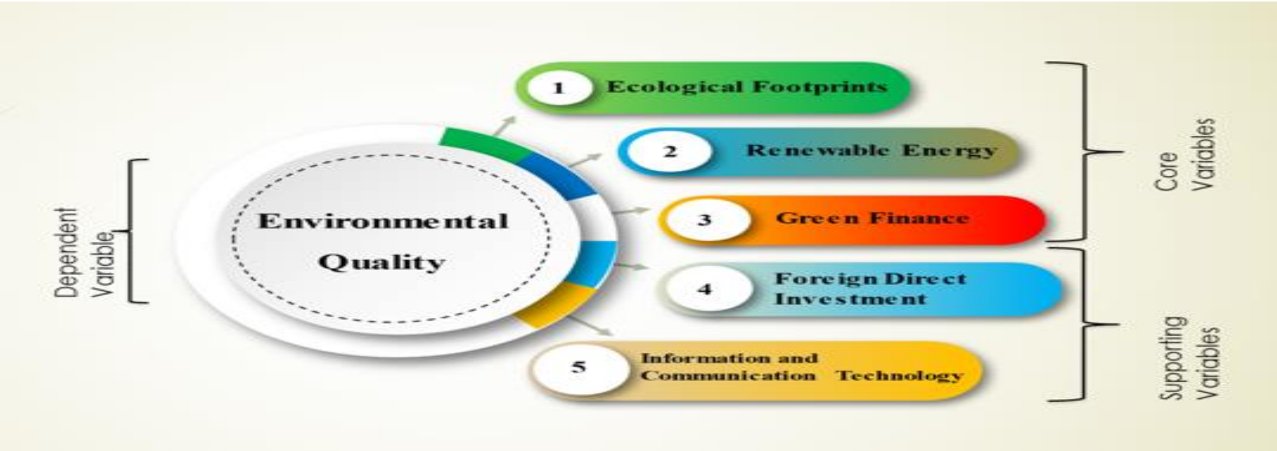
$$CE_{it} = C_0 + \gamma_1 EF_{it} + \gamma_2 GF_{it} + \gamma_3 FDI_{it} + \gamma_4 REEC_{it} + \gamma_5 ICT_{it} + \varepsilon_{it}$$

Here in the equation γ are coefficient of independent variable and ε_{it} are error term.

Table 1: Description of Variables

Variable Names	Acronyms	Measurements	Data Sources	Expected Relationships
Carbon Emissions	CE	Kilotons	World Development Indicator (WDI)	Dependent Variable
Ecological Footprint	EF	Gha (Global Hectares)	Global Footprint Network (GFN)	Positive
Foreign Direct Investment	FDI	Net inflows (Bop, current US$)		Positive
Renewable energy consumption	REEC	% of total final energy consumption		Negative
Green Finance	GF	% of GDP	World Development Indicator (WDI)	Negative
ICT goods imports	ICT	% total goods imports		Positive

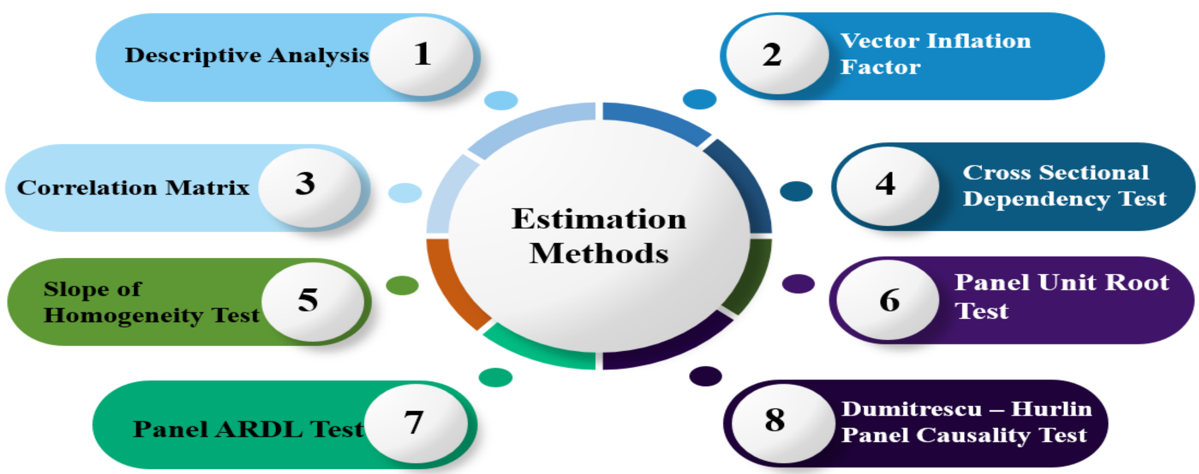
Figure 1: Model



3.3. Empirical Estimation of Model

This study keeps an eye on a simple way of estimation in which procedures are used step by step that are presented in figure 2. Descriptive Analysis, Correlation Matrix and VIF (Vactor Inflation Factor), Cross Sectional Dependency Test, Slope of Homogeneity Test, Panel Unit Root test, Panel ARDL Test and Dumitrescu – Hurlin Panel Causality Test.

Figure 2: Estimation Methods



4. Results and Discussion

4.1. Descriptive Analysis

Descriptive analysis is often the first step in data analysis, helping researchers and analysts understand the data before more advanced statistical techniques are applied. Descriptive analysis is crucial in data exploration and preliminary understanding because it helps analysts identify potential outliers, assess the shape of the data distribution, understand the data's central tendency, and make informed decisions about subsequent analyses. Statistics that offer a clear and comprehensible overview of a dataset are called descriptive statistics. Summary statistics are also known as descriptive statistics (Plaue et al., 2023). They make it possible for researchers and analysts to comprehend the most important aspects of the data without resorting to more sophisticated methods of statistical analysis. This result provides the mean data for CE (302143.10), EF (24.80), GF (4.78742), FDI (350.00), ICT (4.844704), and REEC (60.53063). Based on these findings, one may assume that there is a considerable variation in the SSE of all the series that were investigated for this research. The findings of the analysis indicate that the chosen series have a relatively large standard deviation, which is another finding. To be more exact, the values for CE (643166.7), EF (45.50), GF (10.06672), FDI (883.00), ICT (2.216002), and REEC (21.02394). This likelihood is substantiated by the notably high probability of encountering heterogeneity. To explore the data's normality, statistical measures like kurtosis, the Jarque–Bera test, and probability tests were employed. Once again, the outcomes of these assessments affirm that the research data sample does not conform to a normal distribution.

Table 2: Descriptive Analysis

	CE	EF (Millions)	GF	FDI (Millions)	ICT	REEC
Mean	302143.10	24.80	4.79	350.00	4.84	60.53
Median	21810.00	3.80	0.72	49.30	4.69	54.41
Maximum	2767574.00	180.00	42.90	5320.00	10.81	94.37
Minimum	160.00	0.23	0.04	50000.00	-2.11	19.50
Std. Dev.	643166.70	45.50	10.07	883.00	2.22	21.02
Skewness	2.43	2.13	2.63	3.46	-0.03	0.22
Kurtosis	7.84	6.16	8.81	14.83	3.95	1.78
Jarque-Bera	329.80**	197.17**	429.69**	1314.58**	6.38**	11.69**

4.2. Variance Inflation Factor (VIF) and Correlation Matrix

The Variance Inflation Factor (VIF) for a predictor variable is large, it suggests that the variable is highly associated with other predictor variables and, as a result, may be superfluous to the model. It is possible that it will be essential to address the problem in the event that high multicollinearity is found (that is, when the VIF values are huge; larger than 10).

Table 3: Vactor Inflation Factor

Variables	VIF	1/VIF
EF	5.03	0.198860
GF	1.88	0.532118
FDI	4.35	0.229997
REEC	1.87	0.534940
ICT	2.15	0.464128
Mean VIF		3.06

In the end, the variance inflation test is used in the investigation to assess the problem of multicollinearity that arose throughout the course of this research. According to the findings shown in Table 2, the research model is found to be lacking the high degree of multicollinearity due to the fact that both the mean and individual VIF estimations are found to be less than 10 (Daoud, 2017).

Table 4: Correlation Matrix

	CE	EF	GF	FDI	ICT	REEC
CE	1.00					
EF	0.98	1.00				
GF	-0.19	-0.21	1.00			
FDI	0.92	0.87	-0.16	1.00		
ICT	0.53	0.52	-0.52	0.49	1.00	
REEC	-0.49	-0.52	0.42	-0.45	-0.19	1.00

A table that depicts the correlation coefficients between several different variables is referred to as a correlation matrix. The correlation between each given pair of variables is shown in each individual cell of the matrix (Kavaliauskaite, Thibodeau, Ford, & Yang, 2023). Table 4 showed a list of important information to remember about correlation matrices.

4.3. Coefficient of Slope Homogeneity Test (SHT) and Cross-sectional Dependency (CSD) Test

In panel data analysis, which deals with data containing both cross-sectional and time-series dimensions, test for the homogeneity of regression slopes across different groups or time periods using various statistical tests is required. One common approach is to perform a panel data regression and then conduct a test to check if the slopes of a particular variable are the same across groups or time periods. This study looks at the slope homogeneity test, often known as the SHT, since ignoring this test might increase the risk of making false and skewed forecasts (Campello, Galvao, & Juhl, 2019). As a result, the slope homogeneity test developed by Pesaran and Yamagata (2008) is used in this investigation. This test slope of homogeneity reflects that the slopes are not homogeneous and results are presented in Table 5.

Table 5: Testing for Slope Heterogeneity

Ho: Slope are Homogeneous			
	Delta	p-value	
	-1.991	0.046	Reject Ho
adj.	-2.393	0.017	Reject Ho

As a consequence of this, these issues might occur as a result of a wide variety of factors, including general disruptions, impacts of geography, and unexpected aspects that are peculiar to the nation. Therefore, examining the CSD amongst the key dimensions of the study is vital since it assists in overcoming the inconsistent findings and bias (Mohanty & Sethi, 2022). As a result, the researchers in this study used the CSD test that was developed by Pesaran, Freidman, and frees.

4.4. Cross Sectional Dependency (CSD)

Cross-sectional dependency (CSD) occurs when observations in the same cross-sectional units (e.g., country, firm, region) are dependent on each other and hence violating the key assumption of panel data analysis. There are several tests and diagnostic procedures can be used to detect cross-sectional dependency (Mesagan, Vo, & Emmanuel, 2023). Here, the authors describe a commonly used test called the Breusch-Pagan LM test for CSD that is (Pesaran, 2004). This test is available in Stata and is relatively straightforward to implement. The finding of this result suggested that CSD is not present in among the variables. The second test is Friedman's test that is a nonparametric test. Friedman (1937) test indicates the existence of CSD among variables. Now as results of Pesaran and Friedman tests are contradictory, therefore the third test of Frees' Test is applied for confirmation of presence of CSD. The result of Free' test confirms the presence of CSD as shown in table 6 and indicates the use of second-generation panel unit root tests.

Table 6: Cross Sectional Dependency Results

	Value	**Prob.**
Pesaran	-0.225	1.1782
Friedman	18.616	0.0023**
Frees	0.759	0.0100**
**indicates the presence of cross sectional dependency.		

4.5. Panel Unit Root Tests

Panel unit root tests are statistical procedures that are used in econometrics and time-series analysis to analyses whether individual time series within a panel (a dataset that contains cross-sectional and time-series data) display unit roots. These tests are performed to determine whether or not the panel as a whole exhibit's unit roots. The presence of unit roots is suggestive of the non-stationary nature of a time series, which indicates that the series does not have a fixed mean and that its statistical features fluctuate with time. When it comes to the analysis of panel data, panel unit root tests are of the utmost significance because of the fact that they take into account both the cross-sectional and time-series aspects. Specifically, we looked at whether or not these relationships were stable over time. The CADF & CIPS tests both contribute to the resolution of the problems associated with CSD and eliminate spurious in the process of assessing regression findings.

Table 7: Panel Unit Root Tests

Variables	CIPS I(0)	I(1)	Order	CADF I(0)	I(1)	Order
CE	-1.293	-4.168	1st	-1.665	-2.664	1st
EF	-1.326	-5.764	1st	-1.095	-3.709	1st
GF	-1.563	-3.56	1st	-1.343	-2.158	1st
FDI	-1.905	-4.634	1st	-1.944	-3.602	1st
REEC	-1.187	-5.009	1st	-0.898	-3.473	1st
ICT	-2.091	-5.969	1st	-1.778	-4.666	1st

4.6. Kao Cointegration Test

The Kao test is yet another panel cointegration test that sees widespread use (Mohsin et al., 2023). The two-step Engle-Granger approach is extended to panel data by the use of this method, which is also resistant to cross-sectional dependency. The application of Kao test provides the value of test statistics as well as p-values. These tests are predicated on the hypothesis that cointegration does not take place; hence, the presence of cointegration among the variables can be inferred from a p-value that is low (typically, a number that is less than the significance threshold, such as 0.05). The existence of a cross-sectional dependency, the order of integrating the variables, and any other features that are relevant are all included in these criteria. In addition, in order to guarantee the validity of the study's conclusions and inferences, it is strongly suggested to conduct sensitivity studies and conduct a literature analysis on relevant econometrics.

Table 8: Kao Test for Cointegration

Augmented Dickey–Fuller t			
Ho: No Cointegration among the variables.			
Unadjusted modified Dickey–Fuller t	17.7961	0.0000	Reject Ho
Unadjusted Dickey–Fuller t	-10.8708	0.0000	Reject Ho

4.7. Panel ARDL Test

The Panel Autoregressive Distributed Lag (PARDL) test is a statistical method that assesses the presence of a long-run connection in addition to the short-run dynamics that take place between variables in panel data sets (Zafeiriou, Azam, & Garefalakis, 2022). This test was developed by Zafeiriou and colleagues in the year 2022. Through the use of this test, the autoregressive distributed lag (ARDL) method can be applied to panel data. When we have both time-series and cross-sectional magnitudes in dataset, the PARDL models are helpful for analyzing cointegration and the interaction between variables.

4.8. Long-Run Estimation Models

The short-term and long-term estimators for this study were calculated with the assistance of Panel ARDL, and their results are presented in tables 9 and 10, respectively. It is usually anticipated that FDI and CE will be found to have a favourable relationship with one another. In point of fact, the relationship between FDI and carbon emissions is often analysed with the expectation of observing the nature of FDI. The panel of the study normally has a relationship in which an increase in FDI would bring an increase in carbon emissions (Pata, Dam, & Kaya, 2023; Shao, 2017). It is possible that there is a direct relationship between ecological footprints and CE, and such a relationship can be detected in certain settings; however, the nature of this relationship can vary based on a number of different conditions. According to Alper, Alper, Ozayturk, and Mike (2022); Z. Wang, Bui, Zhang, and Pham (2020), the ecological footprint is a method for measuring the impact that human actions and activities have on the surrounding ecosystem. This impact is measured in terms of the resources that are used up and the waste that is generated as a direct result. According to Caglar et al. (2022), the estimated empirical findings confirm the hypothesis that any endeavour to minimise the EF will also result in a reduction in the CE.

The negative correlation between renewable energy usage and carbon emissions is a well-established fact, with the belief that increasing renewable energy usage leads to a decrease in fossil fuel combustion, a crucial aspect of global climate change efforts (Adebayo, Kartal, Ağa, & Al-Faryan, 2023). Green finance, which supports environmentally friendly projects, is expected to negatively impact carbon emissions in the fight against climate change. ICT can both contribute to and reduce carbon emissions. In South Asian countries, industrial efficiencies, virtual collaborations, and supply chain optimization can help reduce carbon emissions (Cao, Zhang, Li, & Meng, 2023; Meo & Abd Karim, 2022). The long-term cointegration value indicates a convergence towards the desired reduction in carbon emissions, highlighting the complex role of ICT in addressing climate change and sustainability (Ruth, 2011; Zhou, Zhou, Wang, & Su, 2019).

Table 9: Long-Run Estimation Models

Long Run Equation				
EF	0.1181	0.0421	2.8038	0.0062
GF	-0.0438	-0.0053	8.1890	0.0000
FDI	0.0880	0.0214	4.1145	0.0001
REEC	-0.0283	0.0032	-8.9447	0.0000
ICT	0.0193	0.0092	2.1002	0.0385

Table 10: Short Run Estimation Models

Short Run Equation				
COINTEQ01	-0.1795	0.0301	-5.9715	0.0000
D(EF)	0.0195	0.1923	0.1016	0.9193
D (EF (-1))	-0.0288	0.0469	-0.6130	0.5414
D(GF)	-0.2151	0.2231	-0.9644	0.3374
D (GF (-1))	-0.1940	0.1619	-1.1981	0.2340
D(FDI)	-0.0151	0.0107	-1.4135	0.1609
D (FDI (-1))	-0.0123	0.0077	-1.5884	0.1157
D(REEC)	-0.0278	0.0062	-4.4634	0.0000
D (REEC (-1))	0.0029	0.0064	0.4485	0.6549
D(ICT)	-0.0278	0.0248	-1.1192	0.2660
D (ICT (-1))	-0.0212	0.0231	-0.9191	0.3605
C	1.3992	0.3441	4.0658	0.0001

5. Conclusion and Policy Recommendations

The study aims to examine the impact of FDI, ecological footprint, green finance, renewable energy consumption, and ICT on environmental quality in South Asian countries. It uses panel data to analyze dynamic connections. The results show that these factors contribute to a decrease in CE and environmental quality, with green finance and renewable energy consumption having an inverse effect. In summary, while a positive relationship between ecological footprints and carbon emissions is possible, it is inevitable, and it depends on various factors including consumption patterns, energy sources, and policy interventions. Reducing both ecological footprints and carbon emissions is a common goal for sustainability and mitigating climate change. South Asian countries show that increasing renewable energy capacity and usage leads to a decrease in carbon emissions, a crucial aspect of transitioning to a sustainable and low-carbon energy system to combat climate change. Green finance plays a vital role in this transition, with the negative relationship reflecting the positive impact of investments in environmentally friendly projects, technologies, and practices on reducing greenhouse gas emissions.

References

Adebayo, T. S., Kartal, M. T., Ağa, M., & Al-Faryan, M. A. S. (2023). Role of country risks and renewable energy consumption on environmental quality: Evidence from MINT countries. *Journal of Environmental Management, 327*, 116884. doi:https://doi.org/10.1016/j.jenvman.2022.116884

Afshan, S., Yaqoob, T., Meo, M. S., & Hamid, B. (2023). Can green finance, green technologies, and environmental policy stringency leverage sustainability in China: evidence from quantile-ARDL estimation. *Environmental Science and Pollution Research, 30*(22), 61726-61740. doi:https://doi.org/10.1007/s11356-023-26346-1

Agbede, E. A., Bani, Y., Azman-Saini, W. W., & Naseem, N. M. (2021). The impact of energy consumption on environmental quality: empirical evidence from the MINT countries. *Environmental Science and Pollution Research, 28*(38), 54117-54136. doi:https://doi.org/10.1007/s11356-021-14407-2

Akinsola, G. D., Awosusi, A. A., Kirikkaleli, D., Umarbeyli, S., Adeshola, I., & Adebayo, T. S. (2022). Ecological footprint, public-private partnership investment in energy, and financial development in Brazil: a gradual shift causality approach. *Environmental Science and Pollution Research, 29*(7), 10077-10090. doi:https://doi.org/10.1007/s11356-021-15791-5

Ali, R., Rehman, M. A., Rehman, R. U., & Ntim, C. G. (2022). Sustainable environment, energy and finance in China: evidence from dynamic modelling using carbon emissions and ecological footprints. *Environmental Science and Pollution Research, 29*(52), 79095-79110. doi:https://doi.org/10.1007/s11356-022-21337-0

Alper, A. E., Alper, F. O., Ozayturk, G., & Mike, F. (2022). Testing the long-run impact of economic growth, energy consumption, and globalization on ecological footprint: new evidence from Fourier bootstrap ARDL and Fourier bootstrap Toda–Yamamoto test results. *Environmental Science and Pollution Research*, 1-16. doi:https://doi.org/10.1007/s11356-022-18610-7

Asif, M. H., Zhongfu, T., Dilanchiev, A., Irfan, M., Eyvazov, E., & Ahmad, B. (2023). Determining the influencing factors of consumers' attitude toward renewable energy adoption in developing countries: A roadmap toward environmental sustainability and green energy technologies. *Environmental Science and Pollution Research, 30*(16), 47861-47872. doi:https://doi.org/10.1007/s11356-023-25662-w

Caglar, A. E., Guloglu, B., & Gedikli, A. (2022). Moving towards sustainable environmental development for BRICS: investigating the asymmetric effect of natural resources on CO2. *Sustainable Development, 30*(5), 1313-1325. doi:https://doi.org/10.1002/sd.2318

Campello, M., Galvao, A. F., & Juhl, T. (2019). Testing for slope heterogeneity bias in panel data models. *Journal of Business & Economic Statistics, 37*(4), 749-760. doi:https://doi.org/10.1080/07350015.2017.1421545

Cao, M., Zhang, F., Li, J., & Meng, G. (2023). Does climate change surprise the profitability of energy firms? Empirical evidence from China. *Business Strategy and the Environment, 32*(4), 1418-1431. doi:https://doi.org/10.1002/bse.3196

Dai, J., Alvarado, R., Ali, S., Ahmed, Z., & Meo, M. S. (2023). Transport infrastructure, economic growth, and transport CO2 emissions nexus: Does green energy consumption in the transport sector matter? *Environmental Science and Pollution Research, 30*(14), 40094-40106. doi:https://doi.org/10.1007/s11356-022-25100-3

Daoud, J. I. (2017). *Multicollinearity and regression analysis.* Paper presented at the Journal of Physics: Conference Series.

Depren, S. K., Kartal, M. T., Çelikdemir, N. Ç., & Depren, Ö. (2022). Energy consumption and environmental degradation nexus: A systematic review and meta-analysis of fossil fuel and renewable energy consumption. *Ecological Informatics, 70*, 101747. doi:https://doi.org/10.1016/j.ecoinf.2022.101747

Dogan, E., Madaleno, M., & Taskin, D. (2021). Which households are more energy vulnerable? Energy poverty and financial inclusion in Turkey. *Energy Economics, 99*, 105306. doi:https://doi.org/10.1016/j.eneco.2021.105306

Friedman, M. (1937). The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the american statistical association, 32*(200), 675-701. doi:https://doi.org/10.1080/01621459.1937.10503522

Jiakui, C., Abbas, J., Najam, H., Liu, J., & Abbas, J. (2023). Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. *Journal of Cleaner Production, 382*, 135131. doi:https://doi.org/10.1016/j.jclepro.2022.135131

Kavaliauskaite, G., Thibodeau, M., Ford, R., & Yang, Q. (2023). Using correlation matrices to standardise sweet liking status classification. *Food Quality and Preference, 104*, 104759. doi:https://doi.org/10.1016/j.foodqual.2022.104759

Meo, M. S., & Abd Karim, M. Z. (2022). The role of green finance in reducing CO2 emissions: An empirical analysis. *Borsa Istanbul Review, 22*(1), 169-178. doi:https://doi.org/10.1016/j.bir.2021.03.002

Mesagan, E. P., Vo, X. V., & Emmanuel, P. M. (2023). The technological role in the growth-enhancing financial development: evidence from African nations. *Economic Change and Restructuring, 56*(1), 657-680. doi:https://doi.org/10.1007/s10644-022-09442-z

Mohanty, S., & Sethi, N. (2022). The energy consumption-environmental quality nexus in BRICS countries: the role of outward foreign direct investment. *Environmental Science and Pollution Research, 29*(13), 19714-19730. doi:https://doi.org/10.1007/s11356-021-17180-4

Mughal, N., Arif, A., Jain, V., Chupradit, S., Shabbir, M. S., Ramos-Meza, C. S., & Zhanbayev, R. (2022). The role of technological innovation in environmental pollution, energy consumption and sustainable economic growth: Evidence from South Asian economies. *Energy Strategy Reviews, 39*, 100745. doi:https://doi.org/10.1016/j.esr.2021.100745

Murshed, M., Ahmed, R., Kumpamool, C., Bassim, M., & Elheddad, M. (2021). The effects of regional trade integration and renewable energy transition on environmental quality: Evidence from South Asian neighbors. *Business Strategy and the Environment, 30*(8), 4154-4170. doi:https://doi.org/10.1002/bse.2862

Murshed, M., Nurmakhanova, M., Al-Tal, R., Mahmood, H., Elheddad, M., & Ahmed, R. (2022). Can intra-regional trade, renewable energy use, foreign direct investments, and economic growth mitigate ecological footprints in South Asia? *Energy Sources, Part B: Economics, Planning, and Policy, 17*(1), 2038730. doi:https://doi.org/10.1080/15567249.2022.2038730

Nathaniel, S. P., Yalçiner, K., & Bekun, F. V. (2021). Assessing the environmental sustainability corridor: Linking natural resources, renewable energy, human capital, and ecological footprint in BRICS. *Resources Policy, 70*, 101924. doi:https://doi.org/10.1016/j.resourpol.2020.101924

Nawaz, A., Farooq, M., Ul-Allah, S., Gogoi, N., Lal, R., & Siddique, K. H. (2021). Sustainable soil management for food security in South Asia. *Journal of Soil Science and Plant Nutrition, 21*, 258-275. doi:https://doi.org/10.1007/s42729-020-00358-z

Ofori, I. K., & Asongu, S. A. (2021). ICT diffusion, foreign direct investment and inclusive growth in Sub-Saharan Africa. *Telematics and Informatics, 65*, 101718. doi:https://doi.org/10.1016/j.tele.2021.101718

Pata, U. K., Dam, M. M., & Kaya, F. (2023). How effective are renewable energy, tourism, trade openness, and foreign direct investment on CO2 emissions? An EKC analysis for ASEAN countries. *Environmental Science and Pollution Research, 30*(6), 14821-14837. doi:https://doi.org/10.1007/s11356-022-23160-z

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. *Available at SSRN 572504*.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of econometrics, 142*(1), 50-93. doi:https://doi.org/10.1016/j.jeconom.2007.05.010

Raheem, I. D., Tiwari, A. K., & Balsalobre-Lorente, D. (2020). The role of ICT and financial development in CO2 emissions and economic growth. *Environmental Science and Pollution Research, 27*(2), 1912-1922. doi:https://doi.org/10.1007/s11356-019-06590-0

Ruth, S. (2011). Reducing ICT-related carbon emissions: an exemplar for global energy policy? *IETE technical review, 28*(3), 207-211. doi:https://doi.org/10.4103/0256-4602.81229

Shao, Y. (2017). Does FDI affect carbon intensity? New evidence from dynamic panel analysis. *International Journal of Climate Change Strategies and Management, 10*(1), 27-42. doi:https://doi.org/10.1108/IJCCSM-03-2017-0062

Suki, N. M., Suki, N. M., Afshan, S., Sharif, A., Kasim, M. A., & Hanafi, S. R. M. (2022). How does green technology innovation affect green growth in ASEAN-6 countries? Evidence from advance panel estimations. *Gondwana Research, 111*, 165-173. doi:https://doi.org/10.1016/j.gr.2022.06.019

Umair, M., & Yousuf, M. U. (2023). Evaluating the symmetric and asymmetric effects of fossil fuel energy consumption and international capital flows on environmental sustainability: a case of South Asia. *Environmental Science and Pollution Research, 30*(12), 33992-34008. doi:https://doi.org/10.1007/s11356-022-24607-z

Wang, Q.-J., Wang, H.-J., & Chang, C.-P. (2022). Environmental performance, green finance and green innovation: What's the long-run relationships among variables? *Energy Economics, 110*, 106004. doi:https://doi.org/10.1016/j.eneco.2022.106004

Wang, Z., Bui, Q., Zhang, B., & Pham, T. L. H. (2020). Biomass energy production and its impacts on the ecological footprint: An investigation of the G7 countries. *Science of the Total Environment, 743*, 140741. doi:https://doi.org/10.1016/j.scitotenv.2020.140741

Xu, P., Hussain, M., Ye, C., Wang, J., Wang, C., Geng, J., . . . Chen, J. (2022). Natural resources, economic policies, energy structure, and ecological footprints' nexus in emerging seven countries. *Resources Policy, 77*, 102747. doi:https://doi.org/10.1016/j.resourpol.2022.102747

Zafeiriou, E., Azam, M., & Garefalakis, A. (2022). Exploring environmental–economic performance linkages in EU agriculture: Evidence from a panel cointegration framework. *Management of Environmental Quality: An International Journal, 34*(2), 469-491. doi:https://doi.org/10.1108/MEQ-06-2022-0174

Zhou, X., Zhou, D., Wang, Q., & Su, B. (2019). How information and communication technology drives carbon emissions: A sector-level analysis for China. *Energy Economics, 81*, 380-392. doi:https://doi.org/10.1016/j.eneco.2019.04.014