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Do Environmental Innovation and Green Energy Matter for Environmental Sustainability? Evidence from Saudi Arabia (1990–2018)

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Abstract: Climate change and global warming, caused by excessive carbon emissions from transportation and other environmentally hazardous activities, are serious problems for many countries nowadays. Therefore, while some countries are not making optimal use of their resources, others are working hard to preserve a green and clean environment in order to foster long-term growth. Governments and policymakers throughout the world are finally starting to take the risks of climate change and global warming seriously. This paper extends previous literature related to environmental design practices by investigating the impacts of environmental innovation and the deployment of green energy on decreasing carbon dioxide (CO_2) emissions for Saudi Arabia during the period 1990–2018. Different CO_2 emission measures are incorporated in the analysis, namely per capita CO_2 emissions, CO_2 intensity, CO_2 emissions from liquid fuel use, and CO_2 emissions from heat and electricity generation. Overall, the outcomes of the autoregressive distributed lag (ARDL) technique demonstrate the presence of a long-term association between our two main variables (green energy use and environmental innovation) and the different measures of CO_2 emissions, except CO_2 emissions from liquid fuels consumption for green energy use and CO_2 intensity for environmental innovation. In another sense, the use of renewable energies and technologies linked to environmental patents proves to be a good alternative if they do not contribute to environmental pollution. On the basis of the results, this study offers several policy recommendations.

Keywords: environmental innovation; renewable energy; carbon emissions

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1. Introduction

Countries around the world are grappling with serious challenges, including environmental degradation and climate change. Economic activities, such as aggregate household usage and energy generation and usage, are the primary source of pollution due to carbon dioxide (CO_2) emissions [1–6]. Growing domestic consumption adds to CO_2 emissions since it raises energy demand [7–11]. However, energy production and consumption are critical for economies in industrialized countries as well as developing and contemporary economies because they dictate all economic activity. Industries, houses, and cars all need a variety of energy kinds and sources to get things done. Making and using energy has severe implications for the environment since it generates waste, such as radioactive material, and pollutes the air as a result [12–14]. The use of energy systems degrades the environment, pollutes water and air, and has negative effects on human health and marine life, all of which must be considered. For the most part, the environmental impact of energy use, particularly that derived from fossil fuels, is dependent on several factors: the used technology, total energy consumption, efficiency in turning primary energy into a usable form of energy (containing distribution), and the fuel mix used to generate that energy [15].

In the energy mix, the usage of fossil fuels such as coal, natural gas, and crude oil continues to pollute the environment and emit carbon dioxide. One of the main ways to combat global warming is to have a low-carbon economy, and technological innovation in the energy field is seen as a key part of that strategy [16–21]. The term "energy technology innovation" refers to the expansion of science and technology in the energy sector. It also mentions producing innovations intended at boosting the application of new energy-related technology for commercial purposes [22].

Energy characteristics classify energy technology innovations as either renewable or fossil-based, depending on their form of energy [23]. A growing body of evidence indicates that innovations in energy technologies are influencing global energy usage systems. By updating the energy consumption structure, the adoption of sustainable green technologies (such as solar, wind, and biomass) facilitates the shift away from a coal-based economy and offers a practical option to lessen regional reliance on fossil fuels [24,25]. Therefore, researchers and environmentalists believe that environmental technology innovation is a successful solution to decrease CO_2 emissions, and studies have shown the presence of negative correlations [26]. Some other academics disagree about the detrimental associations. According to [27], innovation can cut CO_2 emissions in rich countries but raise their levels in developing economies because of the relevance of a place-bound context. Further, different definitions of environmental innovation have been provided in the literature. It has been employed to refer to all inventions that have good environmental consequences (see, for instance, [28]) or merely those innovations that are targeted to have such benefits (see, for instance, [29]). In order to prevent misunderstanding, "environmental innovation" has been used here to refer to any novel technology or product that has less negative environmental consequences than the alternatives. In addition, ref. [30] revealed an inverse link between CO_2 emissions and environmental innovation by using the GMM methods. Ref. [31] observed in OECD nations that R&D expenditures and clean energy had no clear link with CO_2 emissions. Generally, there is no apparent agreement among scholars on energy technology innovations and CO_2 emissions. Examining the role of environment-related technology innovation and the clean energy source in environmental protection in the Kingdom of Saudi Arabia, for instance, can contribute to the body of knowledge on the subject.

This study aims to fill the knowledge gap by investigating the importance of green energy deployment and environmental innovation to environmental protection in Saudi Arabia. In this context, the development of environmental innovation is crucial for addressing the harmful consequences of environmental degradation and therefore contributes to environmental protection. Three important additions to the literature are made by this study. First, previous research has employed a variety of variables, time periods, and methodologies, and the country's economic structure has shifted dramatically throughout the time period under consideration. It is critical to know just how strong the established connection in the current literature still remains for Saudi Arabia. Second, the current study examines the link between environmental innovation, economic growth, and green energy use for four proxies of environmental protection using multivariate time-series data from 1990 to 2018 in Saudi Arabia that, to the best of our knowledge, have not already been performed in this circumstance. It shows the time series' statistical characteristics and defines the absence or presence of long- and short-run correlations among the determinants in the positive and negative directions. Third, a complete conceptual and empirical framework is established to explain the theoretical relationship between the underlying factors in this study. In this paper, Saudi Arabia was chosen for two major considerations: first, it has experienced a remarkable rise in the number of patents relating to environmental innovation, which is estimated at around 1236 patents during the period 1990–2018 [32]. Second, Saudi Arabia is the first-largest producer of CO_2 emissions per capita in the Middle

East and was one of the world's top ten polluters in 2018. Most of Saudi Arabia's CO_2 emissions derive from fossil fuel use for transportation, heating, and power generation [33].

The remaining part of this paper is subdivided into five sections: Section 2 is devoted to a review of the relevant literature. Section 3 is devoted to empirical methodology. Section 4 emphasizes the exploration of the empirical findings. The conclusion and policy recommendations are involved in Section 5.

2. Literature Review

2.1. Green Energy and Environmental Quality Nexus

There is a significant body of literature that has been published in the topic of energy policy concerning the linkage between energy use or, more precisely, of non-renewable energies and emissions of carbon dioxide (CO_2). In recent years, researchers have been investigating the connection between CO_2 emissions and the use of green energy. The research has taken into consideration a wide range of descriptive variables, together with a diversity of geographic regions, sophisticated econometric tools, and other factors.

In this subsection, we will review this relationship. One of the original pieces of research was performed by [34], who examined the causality literature amongst CO_2 emissions and green energy use in developing economies. Both the long-term conservation assumption and the short-term neutrality assumption are supported by the authors' findings. In the same direction, ref. [35] studied the causal link for five countries of SAARC during 1975–2010, between GDP, renewable energy production, poverty, CO_2 emissions, and natural resource depletion. Using Granger's approach to causality, they discovered proof of growth assumption between them using the FMOLS approach. Ref. [36] also investigated green energy use's role in the world's next fastest emerging economies' economic production and CO_2 emissions. The research uses many reliable econometric panel specifications by introducing yearly data between 1990 and 2012. The results provide empirical evidence of a robust, long-term interaction between the factors. Further, using green energy has been shown to negatively affect CO_2 emissions and positively affect economic growth. The investigation exposes that fossil-fuels-rich countries necessitate the diversification of their energy portfolios through integrating renewable sources of energy that foster environmental performance and sustainability as well as enhance the overall level of air quality while simultaneously lowering the degree to which their economies are susceptible to price fluctuations. Using data for OECD states, ref. [37] analyzed the impact of energy from renewable sources on carbon emissions by including some other pertinent variables. The findings of the empirical research indicate that the utilization of renewable sources of energy is essential in order to preserve the ecosystem. Observed evidence empirically indicates that nations ought to stimulate investment in the green energy sector and education and that research and development programs related to the green energy sector had better be built to guarantee environmental sustainability. For G7 countries, ref. [38] examined the carbon effects of trade, electricity costs, and use of renewables. It appears from their results that the size of exchange has a favorable effect on CO_2 emissions but that clean energies and oil prices have a negative effect.

Recently, ref. [39] studied the impacts of five significant determinants on clean energy use during 1998 and 2018 for the ASEAN + 3 economies to ensure economic and environmental stability. They revealed that economic freedom and pollution have such a negative association with using clean energy. Using non-renewable and renewable energy use as determinant factors, ref. [40] examined how energy consumption affects both income and environment in ASEAN nations performing the innovative technique, namely the moments quantile regression method. Specifically, all quantiles (10th to 90th) showed a reduction in CO_2 emissions when using renewable energy sources; however, this reduction was statistically irrelevant at the higher quantiles (60th to 90th). Findings on panel estimate methodologies (DOLS, FMOLS, and FE-OLS) also support the EKC assumption. According to their findings, a one percent rise in the usage of non-clean energy amplifies CO_2 emissions by 0.29 percent; a one percent rise in clean energy use moderates CO_2

emissions by 0.17 percent, 0.15 percent, and 0.17 percent, respectively, through performing FMOLS, DOLS, and FE-OLS, respectively. Over the period 1970–2018, ref. [41] sought to determine the dynamic impacts of globalization on carbon emissions, as well as the usage of clean and non-clean energy sources for Argentina. For the purposes of this study, the econometric technique explored involves the use of methodologies that are resilient to the existence of structural break issues that may occur in the data. The technique of Maki cointegration, which included various structural breakdowns, demonstrated long-run correlations between clean and non-clean energy usage, carbon emissions, globalization, and economic growth, among other findings. When the tool of autoregressive distributed lag was used to evaluate elasticity, the outcomes exposed that both clean energy use and globalization were associated in short- and long-term drop-in emissions. Using Saudi Arabian data, ref. [9] employed the simultaneous equation modeling technique to investigate the three-way linkage among environmental quality, economic growth, and green energy spanning the year 1990 to 2016. The findings show bidirectional causation between green energy use and CO_2 emissions; nonetheless, the use of green sources in Saudi Arabia did not help to reduce the disparity between improving the economic situation and saving the environment. Within the same framework, ref. [42] reviewed the combined influence of economic growth and green energy on mitigating CO_2 emissions, and they provided support for the results that renewable energy sources only have a marginal effect on slowing environmental degradation. They also confirmed that the combined influence of green energy usage and economic growth on measures of CO_2 emissions is statistically negligible for all the assessed specifications, regardless of the model used, indicating that the share of using green energy is not enough to minimize the detrimental influence of economic expansion on Saudi Arabia's environment, including its level of quality. Further, ref. [43] explored the relationship between the use of renewable energy sources and carbon dioxide emissions during the period of 2000–2015 using data from countries that are quickly urbanizing. They performed this by employing an estimate based on the generalized method of moments (GMM). They found that switching to renewable energy lowers carbon dioxide emissions. Using data from 36 OECD nations spanning 2000–2019, ref. [44] analyzed how adopting energy efficiency and renewable energy initiatives affected their CO_2 emissions. Emissions were reduced due to the use of renewable energy and increased energy efficiency, as estimated by the GMM system. For the effects of renewable technologies, it seems that hydropower and wind energy both help to lower emissions, though to varying degrees. Despite this, solar energy has not been shown to reduce emissions by a statistically meaningful amount. Further, the use of fossil fuels worsens environmental standards.

2.2. Environmental Innovation and Environmental Quality Nexus

The implications of environmental innovation on the environment have received a negligible amount of attention from researchers. Ref. [45] used the simultaneous panel data model to evaluate the correlation between toxic air pollution rates and environmental innovations as part of an empirical study of the connection between environmental protection and environmental innovation. Over the course of 16 years, from 1989 to 2004, a group of 127 US manufacturing companies reported two-directional causal linkages between emissions and environmental innovation. According to the researchers, environmental innovation will play a crucial role in reducing harmful emissions in the US, and stricter emission rules will result in better environmental conditions and larger emissions reductions. Additionally, ref. [46] showed that "greening" suppliers' environmental efficiency is significantly increased by innovation in the field of the environment. Their research suggests that in order to improve environmental efficiency, innovations in environmental processes and commodities may be more effective than innovations in environmental management. The research conducted by [47] confirms the significance and effect of environmental innovation in the case of China, highlighting energy efficiency and R&D as essential factors in bringing about a decrease in carbon dioxide emissions. The results of the latter study are compatible with the findings of [48], which validates the findings of the later study's conclusions. Furthermore, further findings suggest that environmental attitudes and environmental control are beneficial for environmental innovation. Using data for N-11 economies, ref. [49] confirmed that technology innovation has a harmful influence on carbon emissions. This will contribute to the achievement of the COP 21 objectives. In the same context, ref. [50] used a spatial econometric model to assess whether China's CO_2 emissions can be reduced by new energy technology innovations. The findings indicate that while innovative technology related to clean energy sources helps to moderate CO_2 emissions, innovation in the field of fossil energy technologies has been found to be ineffective in lowering carbon dioxide emissions.

Recently, from 1990Q1 to 2016Q4, ref. [13] scrutinized the cyclical influence of technological innovation in the environmental field on CO_2 emissions in the United States. The outcomes display that during the expansion phase, positive shocks in environmental-related technology innovation result in a drop in CO_2 emissions. Similarly, ref. [51] are influential in assessing if innovation, calculated based on the number of patents that have been authorized, benefits or damages the environment in 32 economic sectors and China's 30 provinces. They draw the conclusion that innovative new technologies are more environmentally beneficial than less innovative ones. Ref. [52] also used an ARDL specification to observe the influence of environmental innovation, GDP per capita, the usage of clean energy, and economic openness degree on CO_2 emissions during 23 years in 15 European nations. Their findings demonstrate that environmental innovation has the potential to reduce CO_2 emissions in the long run; however, the observed impact in the short term is the inverse, indicating the possibility of a rebound effect. For the top 10 carbon-emitting economies, ref. [53] investigated how trade, environmental innovation, and renewable energy use affect CO_2 emissions. CS-ARDL (cross-sectionally augment autoregressive distributed lag) approach outcomes display that income, green energy use, and environmental innovation, as well as trade, are major factors in clearing up consumer-based carbon emissions and territorial carbon emissions in the long term. Using data from 37 OECD economies from 1970 to 2019, ref. [54] analyzed the importance of fiscal decentralization, technological innovation in the environmental field, and export diversification in achieving the objective of carbon neutrality. It employs second-generation tests for empirical analysis, which can deal with heterogeneity and cross-sectional dependency difficulties. In order to accomplish this, this study makes use of the most recent cointegration methods. It is necessary to inspect the long-run dynamic equilibrium among the series of interests using the AMG (augmented mean group) technique. According to the findings, CO_2 emissions are amplified in the long run by fiscal decentralization and export diversification, as well as GDP growth. In contrast, the usage of clean sources of energy and the development of environmentally friendly technologies contribute to environmental betterment. Using data for BRICS economies, ref. [55] contribute to the body of current research by identifying the cyclical and asymmetries in the influence of environmental innovative technology on carbon emissions. An important finding from this research was that the economic slump had a major long-term beneficial impact on the development of environmental-related technology and carbon emissions. Second, while the economy is growing, the amount of carbon dioxide emitted is reduced due to positive shocks to environmental technology innovation. Another finding from this study is that shocks of innovation in environmental-related technologies were countercyclical during business cycles. Finally, positive shocks to the innovation process in green technologies had a greater influence on carbon dioxide emissions than negative shocks to the innovation process in green technologies.

3. Empirical Methodology

3.1. Model and Research Strategy

In this paper, we examine the long-term association, also known as cointegration, between green energy consumption (REC), real GDP per capita, foreign direct investment (FDI), environmental patents-related technologies (EPR), urbanization (UBR), and environmental protection. By using a comparative analysis, this last one is proxied by four environmental indicators of CO_2: CO_2 emissions per capita ($CO2_{pc}$), CO_2 emissions resulting from the generation of heat and electricity ($CO2_{elph}$), CO_2 emissions caused by the consumption of liquid fuels ($CO2_{lif}$), and CO_2 intensity ($CO2_{int}$). Hence, the literature review allows us to create for empirical examination the following model:

$$\left\{\begin{array}{c} CO2_{pc} \\ CO2_{elph} \\ CO2_{lif} \\ CO2_{\text{int}} \end{array}\right\} = f(REC_t, GDP_t, FDI_t, EPR_t, URB_t) \tag{1}$$

By utilizing the natural logarithm of the series from Specification (1), the regression to be approximated may be represented as follows:

$$\left\{\begin{array}{c} \ln CO2_{pc} \\ \ln CO2_{elph} \\ \ln CO2_{lif} \\ \ln CO2_{\text{int}} \end{array}\right\} = \beta_0 + \beta_1 \ln REC_t + \beta_2 \ln GDP_t + \beta_3 \ln FDI_t + \beta_4 \ln EPR_t + \beta_5 \ln URB_t + \varepsilon_t \tag{2}$$

where four indicators explain environmental degradation, explicitly per capita CO_2 emissions ($CO2_{pc}$), CO_2 emissions resulting from the generation of heat and electricity ($CO2_{elph}$), CO_2 emissions caused by the consumption of liquid fuels ($CO2_{lif}$), and CO_2 intensity ($CO2_{int}$). REC denotes renewable energy use. GDP refers to per capita real GDP. FDI signifies technology transfer given by net inflows of foreign direct investment. EPR is used as a proxy of environmental patents-related technologies. The urban population is proxied by URB. The long-term elasticity is represented by the parameters β_i and ε_t, error term.

Assuming that there is an increase in REC and the environmental patents-related technologies cause lower CO_2 emissions, $\beta_{1(\text{REC})} < 0$ and $\beta_{1(\text{EPR})} < 0$. Nevertheless, we predicted that a rise in per capita GDP and urbanization cause higher emissions of CO_2 ($\beta_{2(GDP)}$, and $\beta_{5(URB)}$ are positive). In terms of FDI, we predicted CO_2 emissions to have either positive or negative coefficients.

In this study, we employ the ARDL technique, which was first proposed by [56] and then refined by [57]. In case of comparison to certain other tests of cointegration, the ARDL approach is characterized by the feature that it may be used to non-stationary variables without being constrained to the same order of integration as the time series under consideration. As soon as integrated variables of order 0 and 1 are used, the test of cointegration can be performed concurrently on both factors. One other feature of the ARDL model is that it allows for a larger sample size. Indeed, in case of comparison to certain other tests, this model is more appropriate for small samples and enables the generation of more consistent findings in these circumstances. For the equations to be approximated, the general form of the ARDL technique is given below:

$$\begin{aligned} \left\{\begin{array}{c} \Delta \ln CO2_{pc} \\ \Delta \ln CO2_{elph} \\ \Delta \ln CO2_{lif} \\ \Delta \ln CO2_{\text{int}} \end{array}\right\} &= \alpha_0 + \sum_{k=1}^{n} \alpha_{1k} \left\{\begin{array}{c} \Delta \ln CO2_{pc} \\ \Delta \ln CO2_{elph} \\ \Delta \ln CO2_{lif} \\ \Delta \ln CO2_{\text{int}} \end{array}\right\}_{(t-k)} + \sum_{k=1}^{n} \alpha_{2k} \Delta \ln REC_{(t-k)} + \sum_{k=1}^{n} \alpha_{3k} \Delta \ln GDP_{(t-k)} + \sum_{k=1}^{n} \alpha_{4k} \Delta \ln FDI_{(t-k)} + \sum_{k=1}^{n} \alpha_{5k} \Delta \ln EPR_{(t-k)} \\ &+ \sum_{k=1}^{n} \alpha_{6k} \Delta \ln URB_{(t-k)} + \beta_1 \left\{\begin{array}{c} CO2_{pc} \\ CO2_{elph} \\ CO2_{lif} \\ CO2_{\text{int}} \end{array}\right\} + \beta_2 \ln REC_{(t-1)} + \beta_3 \ln GDP_{(t-1)} + \beta_4 \ln FDI_{(t-1)} + \beta_5 \ln EPR_{(t-1)} + \beta_6 \ln URB_{(t-1)} + \varepsilon_t \end{aligned} \tag{3}$$

Furthermore, our methodological approach is divided into three stages: The first checks the stationary characteristics of each variable using the unit root test, which enables the determination of the order of the variables' integration. In this context, the augmented Dickey–Fuller (henceforth ADF) and Phillips and Perron (henceforth PP) stationarity tests by [58,59] will accordingly apply for this objective. After that, the limit testing approach, also known as the bound test ARDL, is used to determine whether there are long-term interactions among factors. The third phase is to assess the short- and long-term input variables as well as to test their stability. Ref. [57] have all developed the ARDL approaches. This approach is characterized by the fact that it does not require that the time series be stable of the same degree, and Pesaran believes that the bound tests can be applied if the time series is stable at the level, i.e., integrated of zero I(0) or integrated of the first degree I(1) or a combination of the two, and the only condition for applying this test is that the time series are not integrated with the second degree, i.e., of the form I(2). The ARDL model is characterized by the fact that it takes a sufficient number of time delay periods and gives better results for the parameters in the long term. We are able to determine the size of the effect that each independent variable has on the dependent variable by using this methodology. In addition, we are able to determine the complementary relationship that exists between the dependent variable and the independent variables in both the long term and the short term within the same equation. Moreover, this methodology is characterized by the presence of highly reliable diagnostic tests.

3.2. Data and Descriptive Statistics

For this work, we utilized yearly data for Saudi Arabia that was gathered from the databases of the World Development Indicators (WDI), with data extending from 1990 to 2018 for these indicators. The description and source of the used series are arranged in Table 1. Likewise, Table 2 displays the main descriptive statistics relating to the variables over the period in question. One of the most important aspects of this table is the normality test (Jarque–Bera). This displays that the null assumption of normality cannot be rejected at 5% for $CO2_{pc}$, $CO2_{int}$, $CO2_{elhp}$, GDP, and urban population variables. Otherwise, the findings of Jarque–Bera tests expose that $CO2_{pc}$, $CO2_{int}$, $CO2_{elhp}$, GDP, and urban population have a normal distribution.

Table 1. Description of variables and expected sign.

Indicators	Variables	Description	Source	Expected Sign
Environmental indicators	**$CO2_{pc}$** **$CO2_{int}$** **$CO2_{elph}$** **$CO2_{lif}$**	CO_2 emissions (metric tons per capita). CO_2 intensity (kg per kg of oil equivalent energy use). CO_2 emissions from electricity and heat production, total (% of total fuel combustion). CO_2 emissions from liquid fuel consumption (% of total).	[60]	N/A
Energy indicator	**REC**	Renewable energy consumption (% of total final energy consumption).	[60]	Negative
Economic indicators	**GDP** **FDI**	GDP per capita (constant 2010 USD). Foreign direct investment, net inflows (% of GDP).	[60]	Positive/Negative
Technology indicator	**EPR**	Environmental patents-related technologies.	[32]	Negative
Demographic indicator	**URB**	Urban population (% of the total population).	[60]	Positive

N/A: not available.

Table 2. Descriptive statistics and pairwise correlations for Saudi Arabia.

	$CO2_{pc}$	$CO2_{elhp}$	$CO2_{lif}$	$CO2_{int}$	REC	GDP	FDI	EPR	URB
Mean	13.631	48.710	74.869	2.526	0.013	19,465.34	1.651	42.620	80.891
Median	12.718	49.102	78.032	2.505	0.009	19,367.58	1.043	2.000	80.979
Max	17.691	50.486	90.023	2.868	0.037	21,399.10	8.496	233.000	84.287
Min	10.249	46.981	49.914	2.367	0.006	16,696.41	−1.307	0.000	76.583
SD	2.288	1.168	10.872	0.113	0.008	1195.413	2.517	71.239	2.142
Skewness	0.435	−0.038	−0.908	1.289	1.746	−0.165	1.311	1.558	−0.183
Kurtosis	1.708	1.479	2.879	4.852	4.881	2.336	3.863	4.216	2.023
Jarque−Bera	2.931	2.414	3.732	10.501	19.012	0.708	9.528	13.527	1.405
Probability	0.230	0.299	0.154	0.005	0.000	0.701	0.008	0.001	0.495
$CO2_{pc}$	1								
$CO2_{elhp}$	−0.265	1							
$CO2_{lif}$	0.248	0.001	1						
$CO2_{int}$	−0.425	−0.322	−0.363	1					
REC	−0.520	−0.410	−0.185	0.855	1				
GDP	0.647	−0.369	0.180	0.128	−0.008	1			
FDI	0.444	−0.302	0.061	−0.404	−0.349	0.217	1		
EPR	0.851	−0.177	0.040	−0.076	−0.275	0.692	0.061	1	
URB	0.900	0.055	0.269	−0.689	−0.782	0.376	0.474	0.675	1

Notes: SD, Min., and Max. are standard deviation, minimum, and maximum, respectively.

In addition to the foregoing, the finding from Table 2 reveals that the range for the environmental indicators is from 10.249 to 17.691 metric tons for per capita CO_2 emissions. In the interval of 46.981 to 50.486 percent of total combusting fuel, CO_2 emissions from electricity and heat generation are actually produced. The utilization of liquid fuel usage results in CO_2 emissions ranging from 49.914 to 90.023 (kt). For the carbon dioxide intensity, the range is 2.367 to 2.868 kg of oil equivalent energy consumption. Aside from that, the proportion of green energy use in total final energy use varies from 0.006 percent to 0.037 percent. Concerning the economic indicators, per capita GDP varies from USD 16,696.41 to USD 21,399; FDI ranges from −1.307 to 8.496% of GDP. Environmental patents-related technologies range from 0 to 233 and urbanization from 76.583 to 84.287% of the total population. Likewise, this table demonstrates that per capita GDP has the strongest link with per capita CO_2 emissions; however, the CO_2 intensity variable has the weakest relationship with GDP per capita. Concerning the environmental indicators, CO_2 intensity has the highest correlation with renewable energy. Apart from that, increasing renewable energy consumption is negatively linked to GDP and associated negatively with three out of four measures of CO_2 emissions, implying that increasing usage derived from green energy sources causes economic growth to slow without worsening environmental conditions.

4. Empirical Results

The following stages are required for the use of the ARDL approach for cointegration analysis: (i) check for time-series stationarity; (ii) determine the most appropriate number of lags; (iii) to establish a long-term relationship, it is necessary to go through the bound test; (iv) compute the long- and the short-term parameters of the regression model; (v) the CUSUM and CUSUMSQ procedures, as well as residue analysis, are used to determine the model's stability.

This study performs the ADF and PP tests of stationarity in order to obtain the integration order of the variables under consideration. We must first confirm that no series of order 2 is integrated because, as presented by [57], the critical values only concern integration levels 0 and 1. Once this is accomplished, we can utilize the bound test. Although it should be noted that performing the bounds test for cointegration is preferred in case the variables are integrated into dissimilar orders I(0) and I(1), this does not rule out the use of the bounds test in circumstances when both variables are integrated in a similar order. Table 3 presents the findings of the assessed tests. Whole variables are shown to be stationary not at level but at the first difference. As a result, they are integrated into the first order.

Table 3. Unit root tests analysis.

Variables	ADF Test		PP Test		Order of Integration
	Level	First Difference	Level	First Difference	
$CO2_{pc}$	−1.495 (0.519)	−1.010 (0.734)	−1.327 (0.602)	−4.162 (0.003) *	I(1)
$CO2_{elph}$	−2.907 (0.059) ***	−7.685 (0.000) *	−2.874 (0.063) ***	−7.685 (0.000) *	I(0)/I(1)
$CO2_{lif}$	−3.105 (0.038) ***	−5.333 (0.000) *	−3.313 (0.024) **	−5.513 (0.000) *	I(0)/I(1)
$CO2_{int}$	−3.864 (0.007)*	−6.931 (0.000) *	−4.135 (0.004) *	−6.931 (0.000) *	I(0)/I(1)
REC	−3.265 (0.026) **	−4.942 (0.000) *	−3.577 (0.013) **	−5.032 (0.000) *	I(0)/I(1)
GDP	−1.932 (0.313)	−5.504 (0.000) *	−2.024 (0.275)	−5.541 (0.000) *	I(1)
FDI	−2.429 (0.143)	−3.865 (0.006) *	−1.637 (0.451)	−3.705 (0.009) *	I(1)
EPR	4.085 (1.000)	1.360 (0.998)	3.536 (1.000)	−5.107 (0.000)*	I(1)
URB	−0.116 (0.938)	−5.302 (0.000) *	−2.933 (0.053) ***	−21.170 (0.000) *	I(0)/I(1)

Note: ***, **, and * show significance at 10%, 5%, and 1%, respectively. The null hypothesis for the PP and ADF tests is that a series has a unit root (is non-stationary).

After defining the order in which the variables are integrated, the following objective is to establish the appropriate number of lags to consider. It is next essential to fix an optimal number of lags for the vector autoregressive (VAR) regression that is accomplished by applying the Akaike information criterion (AIC) criteria and Schwartz information criterion (SIC) (Table 4). For the period 1990–2018, two VAR models (P = 0 and 1) were estimated. One-unit lag is implied by the AIC criteria. In this study, just the last requirement has been taken into consideration.

Table 4. Criteria of selecting lag length for cointegration.

	Lag	LogL	LR	FPE	AIC	SIC	HQ
$CO2_{pc}$	0	75.963	NA	1.85×10^{-10}	−5.381	−5.091	−5.298
	1	226.131	219.476 *	3.09×10^{-14} *	−14.163 *	−12.131 *	−13.578 *
$CO2_{elph}$	0	92.639	NA	1.53×10^{-11}	−7.876	−7.578	−7.806
	1	214.737	166.497 *	7.00×10^{-15} *	−15.703 *	−13.620*	−15.212 *
$CO2_{lif}$	0	92.935	NA	1.49×10^{-11}	−7.903	−7.605	−7.833
	1	206.612	155.014 *	1.46×10^{-14} *	−14.964 *	−12.881 *	−14.474 *
$CO2_{int}$	0	43.819	NA	1.72×10^{-9}	−3.151	−2.857	−3.073
	1	175.415	186.428 *	6.64×10^{-13} *	−11.117 *	−9.056 *	−10.571 *

* Designates lag order selected by the criterion, NA refers to not available. **LR:** Likelihood ratio criterion. **FPE:** Final prediction error. **HQ:** Hannan–Quinn criteria.

To check out the long-term association between the series in the investigation, we use the ARDL approach for cointegration after choosing the optimal lags for the model and the sequence in which the covariates should be integrated. The F-statistic is calculated using the bound test (Table 5). This tests the null assumption that the parameters of the lagged variables in Equation (2) are zero. Concerning the environmental indicators, the F-statistics are equal to 5.212 for $CO2_{pc}$, 6.278 for $CO2_{elph}$, 6.240 for $CO2_{lif}$, and 5.482 for $CO2_{int}$ in comparison to the critical values under and above the 5% and 1% significance levels. The test statistic is higher than the maximum allowable level (3.41 and 4.68, respectively). As a result, we reject the null assumption of the absence of a long-term link and conclude that there is a long-term association between the different variables in the four models.

The [57] approach, which is reliant on the assessment of ARDL modeling techniques, was used to compute the parameters of the short- and long-term association (Equation (3)). As exposed in Table 6, the estimation results reveal that all the parameters of the estimated regression are extremely significant, indicating that the model is reliable (5 percent and even 1 percent in most cases). Likewise, the model is globally significant. In addition, the error correction process is assessed to examine the short-term linkage between the factors. The outcomes demonstrate that the error correction term ECM (−1) displays a statistically significant coefficient, which suggests that the speed with which short-term adjustments attain equilibrium may be made statistically significant. Furthermore, this term has a value of around −0.372 (−0.540), which means that when the CO_{2pc} (CO_{2elph}) are over or under their equilibrium value, they would adjust by 37.2 percent (54 percent) every year, depending on their position. The coefficients of the lag variables serve as a representation for the short-run elasticities. These latter are statistically significant with the predicted signs for all variables and all models, except for renewable energy for the CO_{2lif} and CO_{2int} models, which are not statistically significant. Increasing real GDP per capita and urbanization by 1% each, for example, would result in a 0.060 percent and a 25.040 percent rise in CO_2 per capita, respectively, in the short run. It is obvious that an augmentation in GDP per capita will require augmentation in energy use for the transport of people and goods, for example. Indeed, in the case of Saudi Arabia, individual transport of people is more developed, and the more income increases, the more people tend to afford devices with combustion engines, fueled by gasoline and which emit polluting gases and particles. The rise in wealth will result in augmented demand. In the idea of wanting to meet the added demand, environmental resources will be overexploited and thus cause environmental degradation. In addition to the foregoing, the concentration of the population is growing in the cities of Saudi Arabia. This leads to the development of transport networks and an increase in household waste, a responsible factor affecting the environment. Saudi Arabia is urbanizing in a unique process that weighs heavily on the natural environment of cities and destroys their ecological heritage.

Furthermore, the long-run coefficients, which likewise express long-term elasticities, are shown in the middle of Table 6. According to the statistically significant values of the variable "REC," an increase of 1 percent in green energy use would cause reductions in carbon emissions of 0.185 percent, 0.031 percent, and −0.305 percent, respectively, in the following three categories: $CO2_{pc}$, $CO2_{elph}$, and $CO2_{int}$. This coefficient has a negative sign, which is compatible with the outcomes of [39] for the case of ASEAN +3 economies, ref. [41] for the example of Argentina, ref. [61] for the example of China and the United States and India, ref. [43] for the example of Central/Eastern European countries, and [44] for 36 OECD countries. These studies unequivocally show that a reduction in carbon emissions relates to the utilization of renewable and environmentally friendly forms of energy. Therefore, green sources are proving to be among the most promising solutions available, if not the best, as long as they do not lead to environmental damage, especially for $CO2_{pc}$, $CO2_{elph}$, and $CO2_{int}$. The good distribution of clean energy sources, particularly biomass, hydroelectricity, wind power, and solar, appoint them as an important asset for Saudi Arabia, and they can improve the economic situation and the quality of life and help reduce the burden on the environment.

Table 5. ARDL Bound Test results.

Estimated Model	Bound Testing to Cointegration $CO2_{pc}$				Bound Testing to Cointegration $CO2_{elph}$		
	Optimal Lag Length	F-Stat	Cointegration		Optimal Lag Length	F-Stat	Cointegration
$F_{CO2_{pc}}/[CO2_{pc}/REC, GDP, FDI, EPR, URB]$	1,1,0,1,0,1	5.212 **	**Yes**	$F_{CO2_{elph}}/[CO2_{elph}/REC, GDP, FDI, EPR, URB]$	1,1,1,1,1,1	6.278 *	**Yes**
$F_{REC}/[REC/CO2_{pc}, GDP, FDI, EPR, URB]$	1,0,1,0,1,1	0.742	**No**	$F_{REC}/[REC/CO2_{elph}, GDP, FDI, EPR, URB]$	1,1,1,0,1,1	5.033 **	**Yes**
$F_{GDP}/[GDP/CO2_{pc}, REC, FDI, EPR, URB]$	1,0,0,0,0,1	5.262 **	**Yes**	$F_{GDP}/[GDP/CO2_{elph}, REC, FDI, EPR, URB]$	1,1,0,1,0,1	1.867	**No**
$F_{FDI}/[FDI/CO2_{pc}, REC, GDP, EPR, URB]$	1,0,0,0,0,0	7.236 *	**Yes**	$F_{FDI}/[FDI/CO2_{elph}, REC, GDP, EPR, URB]$	1,0,0,0,0,0	7.044 *	**Yes**
$F_{EPR}/[EPR/CO2_{pc}, REC, GDP, FDI, URB]$	1,0,0,0,1,0	5.462 **	**Yes**	$F_{EPR}/[EPR/CO2_{elph}, REC, GDP, FDI, URB]$	1,0,0,0,1,0	5.840 **	**Yes**
$F_{URB}/[URB/CO2_{pc}, REC, GDP, FDI, EPR]$	1,0,1,1,0,1	8.560 *	**Yes**	$F_{URB}/[URB/CO2_{elph}, REC, GDP, FDI, EPR]$	1,1,1,1,0,1	14.670 *	**Yes**
	Bound testing to cointegration $CO2_{lif}$			**Bound testing to cointegration $CO2_{int}$**			
$F_{CO2_{lif}}/[CO2_{lif}/REC, GDP, FDI, EPR, URB]$	1,0,0,0,1,0	6.240 *	**Yes**	$F_{CO2_{int}}/[CO2_{int}/REC, GDP, FDI, EPR, URB]$	1,0,0,0,0,1	5.482 **	**Yes**
$F_{REC}/[REC/CO2_{lif}, GDP, FDI, EPR, URB]$	1,1,0,1,0,1	1.373	**No**	$F_{REC}/[REC/CO2_{int}, GDP, FDI, EPR, URB]$	1,0,0,0,1,1	0.876	**No**
$F_{GDP}/[GDP/CO2_{lif}, REC, FDI, EPR, URB]$	1,1,0,1,1,0	5.377 **	**Yes**	$F_{GDP}/[GDP/CO2_{int}, REC, FDI, EPR, URB]$	1,0,0,0,0,1	2.313	**No**
$F_{FDI}/[FDI/CO2_{lif}, REC, GDP, EPR, URB]$	1,0,0,0,0,0	6.880 *	**Yes**	$F_{FDI}/[FDI/CO2_{int}, REC, GDP, EPR, URB]$	1,1,0,0,0,0	6.501 *	**Yes**
$F_{EPR}/[EPR/CO2_{lif}, REC, GDP, FDI, URB]$	1,0,0,0,0,0	1.344	**No**	$F_{EPR}/[EPR/CO2_{int}, REC, GDP, FDI, URB]$	1,0,0,0,0,0	1.365	**No**
$F_{URB}/[URB/CO2_{lif}, REC, GDP, FDI, EPR]$	1,0,1,1,0,1	7.316 *	**Yes**	$F_{URB}/[URB/CO2_{int}, REC, GDP, FDI, EPR]$	1,1,1,1,0,1	6.758 *	**Yes**
Significance level	**Lower bound I(0)**			**Upper bound I(1)**			
10%	2.26			3.35			
5%	2.62			3.79			
1%	3.41			4.68			

The selection of optimal lags is implemented on AIC. **Note:** * and ** are rejection of null hypothesis at 1% and 5% levels of significance, respectively.

Table 6. Estimated coefficients from the ARDL models.

	Model 1: $CO2_{pc}$		Model 2: $CO2_{elph}$		Model 3: $CO2_{lif}$		Model 4: $CO2_{int}$	
	Coefficients	**t-Stat**	**Coefficients**	**t-Stat**	**Coefficients**	**t-Stat**	**Coefficients**	**t-Stat**
Short-run results								
ΔlnREC	−0.036	−0.966 *	−0.076	−3.426 *	−0.021	−1.063	−0.084	−0.835
ΔlnGDP	0.060	0.222 *	0.189	1.436 *	0.299174	2.143 **	0.359	0.409 **
ΔlnFDI	0.000	0.094 *	0.000	0.226 *	0.004	1.507 **	−0.040	−1.877
ΔlnEPR	−0.012	−0.862 **	−0.000	−0.115 *	−0.001	−0.212 *	−0.008	−0.186
ΔlnURB	25.040	1.980 *	15.845	1.981 *	2.022	2.296 **	63.757	1.948 ***
ECM(−1)	−0.372	−1.902 ***	−0.540	−2.688 ***	−1.322	−6.772 *	−0.276	−1.475 *
Long-run results								
lnREC	−0.185	−1.404 *	−0.031	−0.534 *	−0.015	−1.052	−0.305	−0.674 *
lnGDP	0.163	0.230 **	0.073	0.280 *	0.226	2.300 **	1.299	0.405
lnFDI	0.035	1.416 *	0.010	1.494 **	0.003	1.525 *	−0.147	−0.982
lnEPR	−0.033	−0.922 **	−0.017	−1.027 *	−0.009	−1.544 *	−0.031	−0.185
lnURB	2.418	0.757 *	2.866	1.520 *	1.529	2.636 **	2.602	0.173 *
Constant	−10.736	−0.627 *	15.670	1.812 ***	5.463	1.867 ***	3.628	0.047 **
Diagnostic test statistics								
LM Test	0.394		0.477		4.640		0.304	
ARCH test	1.137		0.140		0.040		0.117	
Durbin-Watson	1.357		1.735		2.444		2.012	
R-squared	0.971		0.813		0.796		0.709	
Stability Analysis								
CUSUM	Unstable		Stable		Stable		Stable	
CUSUMSQ	Stable		Unstable		Stable		Stable	

Note: ***, **, and * indicate significance levels at 10%, 5%, and 1%, respectively.

Similarly, the long-term elasticity of environmental patents-related technologies (EPR) to environmental protection variables displays a statistically negative and significant coefficient (except $CO2_{int}$), which signifies that a 1% augmentation in EPR would imply a decline in CO_2 emissions. This is in accordance with the outcomes of [13] for the case of the United States, ref. [51] for the case of China's 30 provinces and 32 economic sectors, ref. [62] for the case of United States, ref. [63] for the case of Malaysia, ref. [64] for a representative sample of 15 European nations, who generally found that environmental innovation is going to be a crucial driver in the effort to cut harmful emissions, and it is expected that stronger emission standards would generate environmental improvements, which will lead to additional cuts in emissions. Moreover, the implementation of cutting-edge technologies that are protected by environmental patents is beneficial to the conservation of the natural world because it will make a sizeable contribution to the reduction of carbon emissions in Saudi Arabia. This, in turn, makes the protection of the environment a higher priority. This is primarily the potential role of environmental patents-related technologies in the promotion of green technologies, non-polluting or less polluting, in the context of climate variation and worldwide warming, and the promotion of the transfer of such green technologies in favor of Saudi Arabia.

Even though the model parameters are statistically significant (both individually and globally), it is still necessary to determine whether the model is accurate. As a result, validity checks, such as autocorrelation of error testing, should be implemented on the data. Because of autocorrelation among residuals, inconsistencies in the calculated parameters will occur when there is a correlation between the residuals (since the lagged endogenous variable is included in the regression as an exogenous variable). The results of the various validity tests used are presented in Table 6. In general, the diagnostic tests have revealed that the specifications that have been implemented are acceptable. The tests implemented to determine the existence of ARCH (autoregressive conditional heteroscedasticity) in the assessed specification do not reveal any evidence of a heteroskedasticity problem at the 5 percent threshold of the estimated regression. In addition, the LM-test tests used to determine whether correlated residues were present do not reveal any issues with autocorrelation of errors at the 5% level. Likewise, the adjustment parameters defined by R^2 are between 0.709 and 0.971, respectively, which shows that the model fits well.

Checking the stability of the short- and long-term parameters in the specification (3) is the final stage in ARDL estimation. There are two strategies used: CUSUMQ, which is based on the cumulative sum of squared recursive residuals, and CUSUM, which is based on the cumulative sum of recursive residuals (Figure 1). The results demonstrate that the graph of the statistics of CUSUM and CUSUMQ remains within the range of critical values for the vast majority of models when the 5 percent threshold is reached, indicating a long-term stability of the model coefficients.

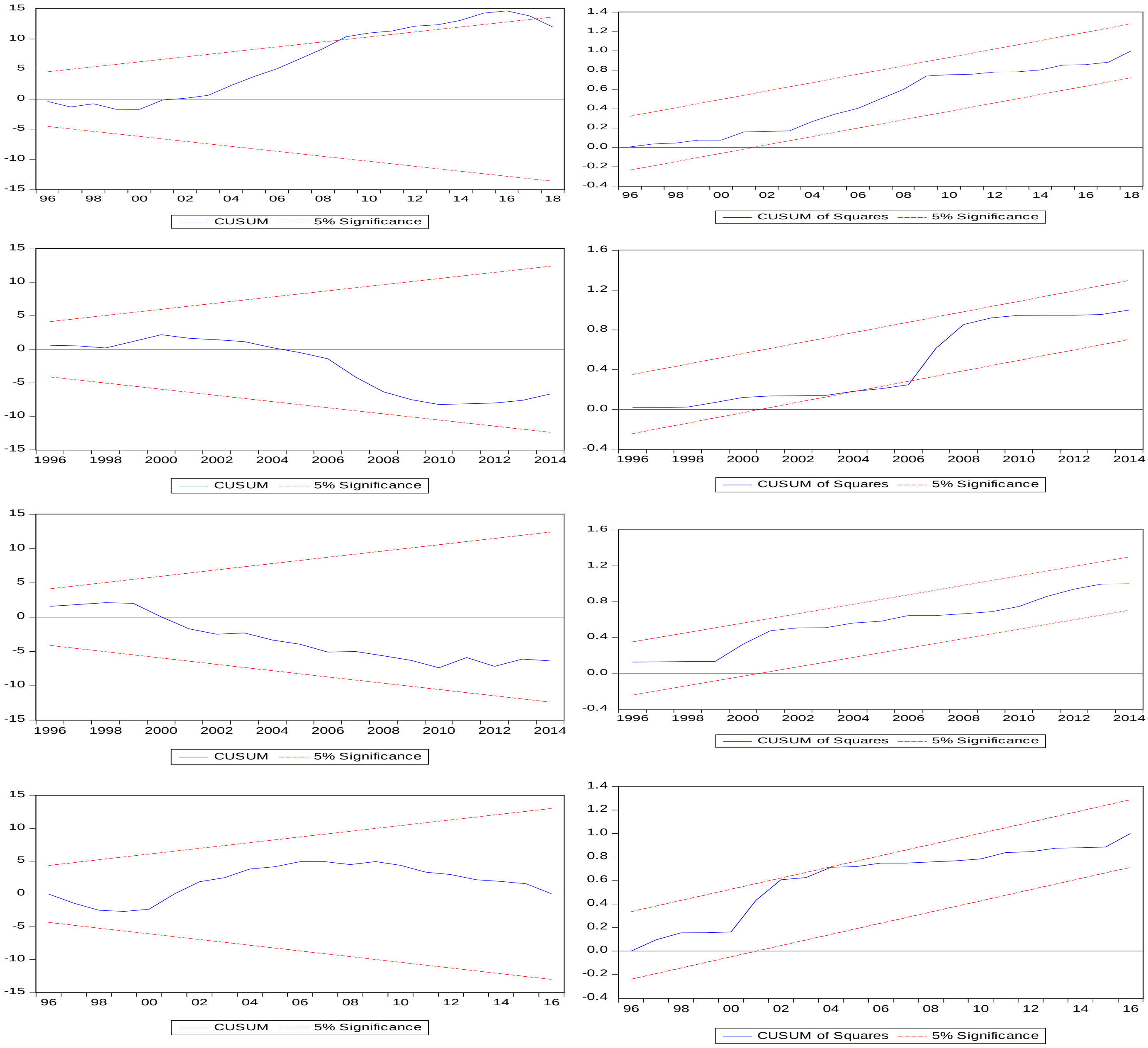

Figure 1. A plot of CUSUM, which is based on the cumulative sum of recursive residuals, and CUSUMQ, which is based on the cumulative sum of squared recursive residuals.

5. Conclusions and Implications

This article examines the role of environmental innovation and green energy deployment in improving the environment in Saudi Arabia during the period 1990–2018. Specifically, this paper explores the long-term relationship, also known as cointegration, between green energy use, real GDP per capita, FDI, environmental patents-related technologies (EPR), urbanization (UBR), and environmental degradation. By using comparative analysis, this last one is proxied by four environmental indicators of CO2 emissions: per capita CO_2 emissions ($CO2_{pc}$), CO2 emissions resulting from the generation of heat and electricity ($CO2_{elph}$), CO_2 emissions caused by the usage of liquid fuels ($CO2_{lif}$), and CO2 intensity ($CO2_{int}$). Further, the ARDL procedure developed by [57] and initially introduced by [56] is also implemented. Overall, the results of the ARDL regression indicate the existence of a long-term linkage between our two main variables (REC and EPR) and the different measures of CO_2 emissions (except $CO2_{lif}$ for REC and $CO2_{int}$ for EPR). An increase of 1% in green energy use would cause reductions in carbon emissions of 0.185%, 0.031%, and −0.305%, respectively, in the following three categories: $CO2_{pc}$, $CO2_{elph}$, and $CO2_{int}$. In addition, the long-term elasticity of EPR to environmental protection variables displays a statistically negative and significant coefficient (except $CO2_{int}$), which signifies that a 1% augmentation in EPR would imply a decline in CO_2 emissions. In another sense, the use of renewable energies and technologies linked to environmental patents prove to be good alternatives, if they do not contribute to environmental pollution. Thus, Saudi Arabia as a rich country is more likely to deploy renewable energy technologies, as it can more readily support the costs of creating new technologies and motivate them with financial rewards. In addition, the results demonstrate that the error correction term ECM (−1) has a significant coefficient showing that the short-term adjustment to equilibrium in terms of speediness is robust. Furthermore, this term has a value of around −0.372 (−0.540), which means that when the $CO2_{pc}$ ($CO2_{elph}$) are over or under their equilibrium value, they would adjust by 37.2% (54%) every year, depending on their position. Interestingly, the findings highly appreciate the contribution of both green energy and environmental innovation in protecting the environment in Saudi Arabia.

According to these findings, the following policies are recommended. First, the expansion of green energy sources. The industrialization process in Saudi Arabia necessitates a large number of natural resources, particularly energy; however, renewable energy can be developed more speedily. Renewable energy production can both meet industrialization's energy demands and help reduce carbon emissions. In fact, the growth of green sources has, without a doubt, contributed to the decline in the level of carbon emissions, and it has the potential to assist considerably to lessen polluted emissions in the foreseeable future [39,43,44]. At this point, policies relating to renewable energy should concentrate on reducing emissions by boosting the proportion of green energy sources and optimizing technologies related to the green energy sector, relocating and reforming polluting industries to increase industrial efficiency and so forth. The optimal link between green energy sources and carbon emissions may be improved experimentally by increasing the share of green energy. There should be more emphasis on regulating the percentage of green energy in Saudi Arabia's energy mix and ensuring that carbon emissions are significantly reduced. Meanwhile, the ideal reduction impact on emissions for renewable energy technology is still in its infancy; thus, Saudi Arabia should actively seek international collaboration and increase the share of energy generated from green sources or decrease the energy intensity. Second, to aid the adoption of innovative environmental legislation to remove the barriers that prevent patents from being completely implemented in the secondary sector, Saudi Arabia should enact environmental laws. In addition, the government should also consider the production per renewable energy unit and focus on ensuring that economic growth and renewable energy development are coordinated. Although current efforts to minimize carbon emissions are minimal, it is possible that increasing the efficiency of green energy sources may become a central focus in the future. In addition, Saudi Arabia should implement measures that encourage the creation of environmental-related patents and speed up their spread across the country. Finally, Saudi Arabia has determined that its economy needs to shift toward energy-intensive industries and services, as well as foster the growth of high technology.

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Abbreviations

Acronyms	**Description**
$CO2_{pc}$	CO_2 emissions (metric tons per capita).
$CO2_{int}$	CO_2 intensity (kg per kg of oil equivalent energy use).
$CO2_{elph}$	CO_2 emissions from electricity and heat production, total (% of total fuel combustion).
$CO2_{lif}$	CO_2 emissions from liquid fuel consumption (% of total).
REC	Renewable energy consumption (% of total final energy consumption).
GDP	GDP per capita (constant 2010 USD).
FDI	Foreign direct investment, net inflows (% of GDP).
EPR	Environmental patents-related technologies.
URB	Urban population (% of the total population).
ARDL	Autoregressive Distributed Lag.
OECD	Organization for Economic Co-operation and Development.
R&D	Research and development.
IEA	International Energy Agency.
SAARC	South Asian Association for Regional Cooperation.
FMOLS	Fully Modified Ordinary Least Square.
ASEAN +3	Association of Southeast Asian Nations Plus Three.
ASEAN	Association of Southeast Asian Nations.
DOLS	Dynamic ordinary least square.
FE-OLS	Fixed-effects ordinary least square.
EKC	Environmental Kuznets Curve.
GMM	Generalized method of moments.
US	United States.
CS-ARDL	Cross-sectionally augment autoregressive distributed lag.
AMG	Augmented mean group.
BRICS	Brazil, Russia, India, China, and South Africa.
PP	Phillips and Perron unit root test.
ADF	Augmented Dickey–Fuller unit root test.
WDI	World Development Indicators.
CUSUM	Cumulative sum of recursive residuals.
CUSUMSQ	Cumulative sum of squared recursive residuals.
VAR	Vector autoregressive regression.
SIC	Schwartz Information Criterion criteria
AIC	Akaike Information Criterion.
LR	Likelihood ratio criterion.
FPE	Final Prediction Error.
HQ	Hannan–Quinn criteria.
ECM	Error correction term.
ARCH	Autoregressive Conditional Heteroscedasticity.

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