energies

MDPI

Article

Do Nuclear Energy, Renewable Energy, and Environmental-Related Technologies Asymmetrically Reduce Ecological Footprint? Evidence from Pakistan

Muhammad Usman [1], Atif Jahanger [2,3], Magdalena Radulescu [4,5,*] and Daniel Balsalobre-Lorente [6,7]

1 Institute for Region and Urban-Rural Development, Center for Industrial Development and Regional Competitiveness, Wuhan University, Wuhan 430072, China; usman399jb@gmail.com
2 School of Economics, Hainan University, Haikou 570228, China; atif_jahanger@hotmail.com
3 Institute of Open Economy, Haikou 570228, China
4 Department of Finance, Accounting and Economics, University of Pitesti, 110040 Pitesti, Romania
5 Institute for Doctoral and Post-Doctoral Studies, University "Lucian Blaga" Sibiu, 550024 Sibiu, Romania
6 Department of Political Economy and Public Finance, Economic and Business Statistics and Economic Policy, University of Castilla-La Mancha, 13001 Ciudad Real, Spain; daniel.balsalobre@uclm.es
7 Department of Applied Economics, University of Alicante, 03690 Alicante, Spain
* Correspondence: magdalena.radulescu@upit.ro

Abstract: Can Pakistan's environmental-related technologies (ERT) and nuclear and renewable energy mitigate environmental pollution? As global warming and climate change rise dramatically, economies shift to friendly energy substitutions and eco-friendly technologies, contributing to the mitigation of environmental contamination. In this scenario, policy and academic analysts have paid more concentration to renewable and nuclear energy deployment with ERT installation. To achieve this goal, the present study scrutinizes the asymmetric effects of nuclear energy, renewable energy, and ERT on the ecological footprint of Pakistan. The current research applies a novel non-linear autoregressive distributive lag method from 1991 to 2020. The results of the current analysis show that negative changes in nuclear energy increase emissions levels in the long run, while positive and negative changes in renewable energy deployment significantly overcome the burden on the environment. Similarly, positive and negative changes in ERT reduce pollution levels in the long run. Moreover, these long-run outcomes are analogous to short-run findings for Pakistan. Therefore, there is a dire requirement to increase the consumption of renewable and nuclear energy sources and take advantage of the noteworthy impact of an uncontaminated atmosphere through clean ERT potentials.

Keywords: ecological footprint; nuclear energy; renewable energy; environmental-related technologies; NARDL model; Pakistan

check for updates

Citation: Usman, M.; Jahanger, A.; Radulescu, M.; Balsalobre-Lorente, D. Do Nuclear Energy, Renewable Energy, and Environmental-Related Technologies Asymmetrically Reduce Ecological Footprint? Evidence from Pakistan. *Energies* **2022**, *15*, 3448. https://doi.org/10.3390/en15093448

Academic Editor: Luisa F. Cabeza

Received: 4 April 2022
Accepted: 5 May 2022
Published: 9 May 2022

1. Introduction

Environmental challenges increase due to rapid industrialization and economic growth in the developing world. Continuous economic growth demands more energy consumption, mainly from fossil fuels, and consequently, greenhouse gas (GHG) emissions are increasing. Yang et al. [1] argued that carbon dioxide (CO_2) emissions, though constituting a large portion of global GHG emissions, may be inadequate to replicate and explore the entire environmental degradation. Pakistan's share of global emissions in 1974 was 0.07%, and in 2016 it increased to 0.50% [2,3]. Pakistan is mainly responsible for increasing global warming and climate change. Therefore, Pakistan must take swift action to meet the Paris Pact of the 2 °C target [4]. For the last few decades, Pakistan's economy has faced adverse effects of global warming, which is displayed in floods, the spread of diseases, etc.

Consequently, it is crucial to understand the actual forces behind the increasing emissions and formulate eco-friendly policies to cope with this issue. Some researchers argue that CO_2 emissions do not account for pollution in forests, soil, mining, etc. [5,6]. The ecological footprint has been recommended in the existing literature to overcome this issue. The ecological footprint measures the total human activities on the environment in six major areas, namely *"forest land, fishing grounds, cropland, carbon footprint, grazing land, and build-up land"*. Therefore, the ecological footprint provides a better and single measurement of environmental degradation and sustainability [7,8].

Fossil fuel-based energy consumption is a threat to global sustainability [9,10]. According to the World Bank [11], the contribution of Pakistan to fossil fuel-based energy utilization, which is the percentage of total utilization, increased from 35.6 in 1971 to 61.5 in 2014 (compared to 61.6% in 1971) [11]. Reducing energy consumption to curtail environmental hazards is not viable as energy is the primary input in all production processes [12]. The United Nations General Assembly (UNGA) set various Sustainable Development Goals (SDGs) in 2015 to ensure a sustainable future. Among others, SDG 7 aims to increase the use of clean energy and reliance on renewable energy to ensure energy efficiency. It is also evident that ensuring SDG 7 is linked to other goals [13,14]. The new United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Agreement call for the reduction of GHG emissions and promotion of renewable and nuclear energy. Hence, Pakistan can achieve long-term goals for a sustainable environment without compromising its socio-economic developmental goals. Renewable energy, particularly nuclear energy, ensures Pakistan's energy security.

Nuclear energy use is well-known as a low environment degradation-related energy source. In the last few decades, nuclear energy utilization has increased by more than 40%, producing 12% of the world's electricity and used for approximately 5% of the world's prime energy demands in 2018 [15,16]. Since the announcement of the Paris agreement, renewable and nuclear energy utilization has increased extensive consideration. Numerous researchers, such as Sadiq et al. [17], Baek [18], Bandyopadhyay and Rej [19], and Lau et al. [20], proposed that nuclear energy utilization can overcome energy security and ecological damages. On the other hand, nuclear power stations require massive capital costs and enormous infrastructural development, which are scarce in developing economies (such as Pakistan) [21]. Pakistan's economy needs extreme actions for an energy revolution. Pakistan's reason for increasing nuclear power stations is to support the increasing energy demand. Pakistan has two nuclear power stations situated at Karachi (90 Megawatt) and Chashma (300 Megawatt). The five operatable reactors produce around 1318 megawatts, and two plants are under construction [11]. Pakistan is one of the seven nuclear nations worldwide [22]. Pakistan faces challenges such as an energy crisis, energy efficiency, and environmental damage, which require essential policy-level solutions rapidly.

Another crucial point of the present study is to include environmental-related technological innovation to inspect the source of contaminant pollution and determine the environmental sustainability of Pakistan's economy. Environmental technology, clean technology, or green technology is the application of one or more environmental monitoring, green chemistry, environmental science, and electronic procedures to monitor, model, and conserve the natural resources and environment, and to reduce the adverse influence of human activities. Environmental-related technologies are also used to describe sustainable energy production equipment such as wind turbines, photovoltaics, etc. However, sustainable development is the center of environmental technologies. The term environmental technology is also used to portray a class of electronic products that can encourage the sustainable management of resources. Advanced technologies can enhance the efficiency of conventional energy sources and also help to promote the development/adoption of cleaner (eco-friendly) energy sources. Moreover, environmentally allied technologies can handle waste discharged by human activities successfully. In the last few decades, technological innovations have been measured as an essential source of dealing with environmental problems [23]. Becoming eco-friendly has become a central goal of every nation as it relates to the political, economic, and social problems of an economy. Rahman et al. [24] recommended that structural reforms and technological progress support handling environmental concerns. Considering these three properties (i.e., nuclear energy, renewable energy, and technology) examined above, three main research questions are to be scrutinized in the present study. First, what is the significant impact of nuclear energy on the ecological footprint of Pakistan? Second, how does renewable energy influence the ecological footprint of Pakistan? Third, to what extent do environmental-related technologies affect the environment in Pakistan?

The reasons for selecting Pakistan are numerous: First, Pakistan heavily depends on fossil fuels (coal, petroleum, natural gas, etc.) for energy accessibility. A continuous gap between energy demand and supply has been predominant in the last three decades, hence leading to extensive social and economic damages. Pakistan has suffered a loss of approximately 6.5% gross domestic product (GDP) (around USD 18 billion) in the fiscal year 2015 alone due to energy deficiency [25]. Second, Pakistan is the 6th most populous nation and 7th largest producer of nuclear energy in the world but still faces an energy crisis [22]. Third, it is predictable that the primary electricity utilization demand will be triple in 2030 [26,27]. Thus, Pakistan is in a very ominous situation, where a mutual shortage of energy issues and environmental damages needs policy-level remedies quickly. Regarding the current and future situation, it is crucial to examine the nuclear energy use in economic growth and environmental extenuation within specific conditions of Pakistan which have an increasing need for nuclear energy use and growth. Due to different geopolitical circumstances, legal limitations, economic development patterns, and environmental strategies on nuclear energy utilization across different nations, many researchers recommended that country-wise examination is important in estimating the role of nuclear energy use on the environment in the case of Pakistan.

By employing a novel approach, the present study contributes the following to the extant body of knowledge in environmental economics. Firstly, we scrutinize the asymmetric effect of nuclear energy use, renewable energy utilization, and environmental-related technologies on the ecological footprint of Pakistan over the period 1990 to 2020. Secondly, this is the first study—according to the author's knowledge—to explore nuclear energy use, environmental-related technologies, renewable energy utilization, and ecological footprint nexus by considering the asymmetric relationships. Thirdly, early researchers mainly focused on CO_2 emissions as a substitution for environmental damages, which numerous researchers broadly criticize. Hence, the current study uses the ecological footprint, which comprehensively embodies environmental excellence proxy and gives more inclusive insight to policymakers, in this case, in Pakistan. Fourthly, the current study used non-linear autoregressive distributive lag (NARDL) to discover short-run and long-run effects.

The remaining part of the paper is presented as follows. The previously published literature relevant to this study is discussed in Section 2. Section 3 provides details of methodology, data, along with the discussion on the model specification. Then, Section 4 provides the empirical conclusions, and finally, Section 5 documents the conclusion and important policy recommendations.

2. Literature Review

The empirical link between nuclear energy (NEC), renewable energy (RECC), non-renewable energy (NRECC), environmental-related technologies (ERT), and ecological footprint (EFP) has been recognized in numerous existing published articles. However, the literature has been divided into pairwise studies associated based on earlier projected outcomes among the variables specified in the following parts.

2.1. Nexus between Nuclear Energy and Environment

Nuclear energy (NEC) is assumed to substitute the conventionally consumed fossil fuel energy that abundantly emits CO_2 emissions into the environment [28]. Several ambiguous pieces of evidence about the impact of NEC and environmental degradation have been documented. For example, Hassan et al. [29] inspected the influence of NEC and technological innovations (TECH) on environmental pollution. The ARDL analysis shows that NEC is a clean energy source, while technological innovation is also helpful for reducing environmental damages. Furthermore, Kartal [30] applied the Multivariate adaptive regression splines to inspect the influence of NEC and environmental decay in the case of the top-five carbon-producing nations. The outcomes revealed that NEC increases environmental decay in some of these nations. Additionally, Sadiq et al.'s [17] empirical conclusions specify that nuclear energy promotes environmental sustainability. Further, Rehman et al.'s [31] results found that nuclear sources negatively affect Pakistan's economic growth. Bandyopadhyay et al.'s [19] outcomes also highlight that NEC implementation can help overcome the environmental damages in the case of India. Some of the existing studies that have found a negative link between NEC and environmental decay include Saidi and Omri [32], Baek and Pride [33], and Ulucak and Erdogan [34]. In contrast, numerous earlier studies have also shown the adverse effects of NEC on environmental degradation, for example, Usman et al. [35], Sarkodie and Adams [36], and Mahmood et al. [21].

2.2. Nexus between Technological Innovation-Environment

With the increasing fear of global climate change, the association between TECH and environmental degradation has generated considerable discussion over the last two decades. Most researchers believe that TECH helps minimize environmental pollution and enhance environmental performance. For example, Bilal et al. [37] demonstrate that in the long run, TECH has a favorable effect on the environment in the case of OBOR nations. Additionally, Jahanger et al.'s [9] outcomes show that natural resources and financial development enhance environmental damages, while TECH reduces environmental degradation. Furthermore, Lin and Ma's [38] results show that TECH can reduce environmental damages indirectly through industrial structure advancement. Moreover, Yang et al. [39] argued that TECH is a vital aspect of reducing environmental decay levels in the case of BICS nations. Other scholars believe that TECH may be degrading environmental performance. For example, Usman and Hammar [23] examined the relationship between TECH and environmental degradation for Asia Pacific Economic Cooperation (APEC) during the 1990–2017 periods. The outcomes of this study demonstrate that TECH enhances environmental pollution. In addition, Cheng et al.'s [40] results indicate that TECH can enhance environmental decay in the case of OECD countries. Additionally, Chen and Lee [41] noted that TECH has no significant mitigation effect on environmental decay in the case of the 96 nations. Moreover, Lin and Ma [38] argued that TECH could minimize environmental pollution indirectly through industrial structure advancement.

2.3. Nexus between Renewable Energy Utilization and Environment

Dogan and Ozturk [42] examined the links between environmental degradation, renewable (REC) and non-renewable energy (NREC) use in the USA. They found that increases in REC mitigate environmental degradation, whereas rises in NREC contribute to environmental damages. Furthermore, Usman and Makhdum [6] used the second-generation technique to study the dynamic links between REC, NREC, FD, and environmental degradation for BRICS-T nations and found that NREC and FD produce environmental degradation, while REC significantly improves environmental performance. Additionally, Usman et al. [7] analyzed the dynamics between REC, NREC, and environmental degradation in a panel of twenty Asian nations. The result of the AMG demonstrated that NREC significantly accelerates environmental pollution, while REC reduces environmental deprivation. In addition, Usman et al. [43] studied the effect of REC and NREC on the 15 highest-emitting nations' CO_2 emissions over the 1990–2017 period and, using the AMG approach, found that REC significantly contributes to minimizing environmental pollution, while NREC is more responsible for the environmental degradation.

Table 1 displays the extant literature in which the nexus between nuclear energy, renewable energy, environmental-related technologies, and environmental damages has been studied. There is hardly any study on Pakistan that used the NARDL model to investigate the nexus of nuclear energy, renewable energy, environmental-related technologies, and environmental damages.

Table 1. Summary of the existing published literature between NEC, REC, and ERT-environment nexus.

Authors	Countries	Duration	Variables	Techniques	Outcomes
(A) Nexus between nuclear energy and environment					
Hassan et al. [29]	China	1985–2018	NEC, TECH, CO_2	ARDL regression	NEC is a clean energy source, while TECH is also helpful for decreasing environmental degradation.
Kartal [30]	Top-five carbon generating nations	1965–2019	NREC, NEC, REC, CO_2	MARS regression	NREC, NEC, and REC usage have mixed environmental pollution effects.
Saidi and Omri [32]	15 OECD nations	1990–2018	NEC, REC, CO_2	FMOLS	Both NEC and REC reduce environmental degradation for the panel estimations.
Baek and Pride [33]	6 nations	1990–2007	NEC, INC, CO_2	MCVAR	NEC reduces environmental poverty in all nations, while INC only increases environmental damages in some economies.
Dong et al. [44]	China	1993–2016	NEC, REC, NREC, CO_2	Granger causality	The outcomes also show that NEC and REC significantly reduce CO_2 emissions while NREC enhances them.
Hassan et al. [28]	BRICS nations	1993–2017	NEC, REC, CO_2	CUP-FM, CUP-BC	NEC reduces environmental pollution while REC corrects environmental degradation in panel countries.
Ulucak and Erdogan [34]	15 OECD nations	2005–2016	NEC, CO_2	D-K regression	NEC is helpful to reduce production-based environmental pollution.
(B) The technological innovation-environment nexus					
Rahman et al. [24]	22 developed nations	1990–2018	REC, CO_2, TECH	NARDL, PMG	Bidirectional causality exists among REC and CO_2, TECH and CO_2, GDP and REC, and REC and TECH.
Bilal et al. [37]	OBOR nations	1991–2019	TECH, CO_2	DSUR	TECH reduces the environmental damages only in OBOR.
Jahanger et al. [9]	73 developing nations	1990–2016	NR, FD, TECH, GDP, EFP	PMG	NR and FD increase environmental pollution while TECH reduces environmental degradation. Furthermore, The EKC hypothesis for the environment is valid for developing nations.
Huang et al. [45]	E-7 and G-7 nations	1995–2018	ICT, ECX, HC, REC, EFP	AMG, and CCEMG	ICT, ECX, and HC upsurge the pollution level while REC significantly reduces it.
Yang et al. [39]	BICS	1990–2016	RMTT, FD, TECH, EFP	AMG and CCEMG	RMTT and FD significantly worsen the environment, while TECH is a vital factor in reducing pollution levels.
Chen and Lee [41]	96 countries	1996–2018	TECH, CO_2	Spatial econometric	TECH has no significant mitigation effect on CO_2
(C) The renewable energy utilization-environment nexus					
Dogan and Ozturk [42]	USA	1980–2014	REC, NREC, CO_2	ARDL	Increases in REC mitigate environmental degradation, whereas increases in NREC contribute to environmental pollution.
Usman and Makhdum [6]	BRICS-T	1990–2018	NREC, FD, REC, EFP	AMG, and CCEMG	NREC and FD lead to produce environmental while FR and REC significantly improve environmental quality.

Table 1. *Cont.*

Authors	Countries	Duration	Variables	Techniques	Outcomes
Usman et al. [7]	20 Asian nations	1990–2014	GDP, NREC, REC, EFP	AMG	GDP and NREC significantly enhance the environmental damages, while REC reduces the total environmental damages.
Usman et al. [43]	15 highest emitting nations	1990–2017	FD, REC, TRD, GDP, NREC, EFP	AMG	FD, REC and TRD significantly minimize environmental pollution, while GDP and NREC are more responsible for environmental degradation.
Wan et al. [46]	India	1990–2018	ECX, GLO, REC, GDP, NREC, EFP	ARDL	ECX, GLO, and REC play a dominant role in abating environmental damages, while GDP and NREC are more accountable for cumulative the pollution level
Usman et al. [47]	7 South Asian countries	1995–2017	CO_2, AGR, TOU, GDP, REC, NREC	FMOLS, and DOLS	AGR, GDP, NREC, and TOU increase the pollution level. However, REC has the ability to protect the environment.

3. Data, Model Design and Empirical Methodology

3.1. Data and Model Arrangement

The present research uses annual data on the ecological footprint (proxy of environment quality), nuclear energy consumption, renewable energy consumption, and environmental-related technologies. The ecological footprint is measured in global hectares per capita (GHApc), nuclear energy consumption is measured in terms of in terms of Terawatt hours (TWh), renewable energy is taken in terms of % of final energy consumption, and development of environmental-related technologies is computed in terms of % all technologies. Ecological footprint data is obtained from the global footprint network [48]. Nuclear energy data is collected from the Statistical Review of World Energy from British Petroleum [49]. Renewable energy consumption and environmental-related technologies databases are obtained from the World Bank [50] and Organization for Economic Cooperation and Development Statistics [51], respectively. Furthermore, the study time period is selected based on the available data from 1990 to 2020. Table 2 portrays the description of the study variables, their unit of measurement, and related data source.

Table 2. Variable description, measuring unit, and data sources.

Variables	Description	Unit of Measurement	Data Sources
EFP	Ecological footprint	Global hectares per person (GHpc)	GFPN [48]
NEC	Nuclear energy use	Terawatt hours (TWh)	BP [49]
REC	Renewable energy use	% of total final energy use	WDI [50]
ERT	Environmental-related technologies	% all technologies	OECD [51]

Furthermore, to examine the asymmetric effect of nuclear energy use, renewable energy use, and environmental-related technologies on ecological footprint, the following linear equation (Equation (1)) can be applied as follows:

$$\mathrm{EFP_t} = f\ (\mathrm{NEC_t},\ \mathrm{REC_t},\ \mathrm{ERT_t}) \tag{1}$$

where EFP denotes the ecological footprint, NEC represents nuclear energy consumption, RE shows the renewable energy consumption, and environmental-related technologies are presented in terms of ERT. All the data series is converted to a natural logarithmic structure to acquire more efficient and robust estimations by eradicating scaling differences of series and heteroscedasticity and normalizing them.

$$\mathrm{Ln(EFP_t)} = \beta_0 + \beta_1\mathrm{Ln(NEC_t)} + \beta_2\mathrm{Ln(REC_t)} + \beta_3\mathrm{Ln(ERT_t)} + \varepsilon_t \tag{2}$$

This research scrutinizes the asymmetric influence of nuclear energy, renewable energy, and environmental-related technologies on the ecological footprint in the case of Pakistan. This research contributes to fulfilling the research gap by including the existence of the suppressor impact manipulated by related environmental technologies on the ecological footprint. Furthermore, the current research applies an environmental-related technology dynamic process in the V-finite lag distribution structure framework, suggested by De Leeuw [52], to verify the optimal and encouraging influence of the environmental-related technologies in Pakistan. This proposal would validate a superlative, appropriate, and possible impact of environmental-related technologies on the ecological footprint. For this aim, the time series presentation of Equation (1) can be transformed in Equation (3) as:

$$\mathrm{Ln}(\mathrm{EFP_t}) = \beta_0 + \beta_1 \mathrm{Ln}(\mathrm{NEC_t}) + \beta_2 \mathrm{Ln}(\mathrm{REC_t}) + \beta_3 \mathrm{Ln}(\mathrm{ZERT_t}) + \varepsilon_t \quad (3)$$

where t shows the time periods, β_0 shows the consent term, and μ_{it} indicates the stochastic error term. Furthermore, $\beta_1 - \beta_3$ show the unidentified independent variables parameters (i.e., NEC, REC, and ZERT) to be estimated.
where:

$$\mathrm{ZERT_t} = *\mathrm{ERT_{t-j}} \quad (4)$$

In Equation (4), ($\mathrm{ERT_{t-j}}$) acquires vigorously dynamic environmental-related technologies at order (4) of the finite V-lag distribution structure that shows the accumulation of environmental-related technologies over the t time.

As we discussed earlier, the current research includes De Leeuw's approach and has malformed the series of environmental-related technologies into a V-finite lag distribution structure (see Figure 1), where we noted that the most favorable effect of environmental-related technologies on ecological footprint (coming into view at t − 2 and the most advantageous lag) is preferred according to Equation (5) as:

$$\mathrm{ZERT_t} = \sum_{i=0}^{k/2} (i+1)\mathrm{ERT_{t-i}} + \sum_{i=k/2+1}^{k=4} (k-i+1)\mathrm{ERT_{t-i}} \quad (5)$$

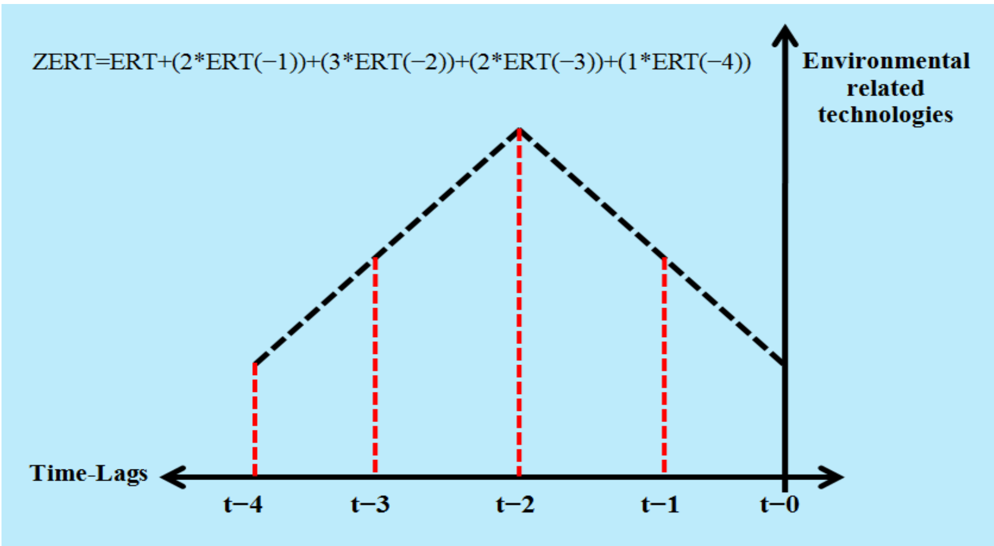

Figure 1. De Leeuw's Finite Lags Distribution Scheme for Environmental-related technologies.

Consequently, we transform Equation (2) into Equation (6) to sophisticate the environmental-related technologies series up to 4 lag distribution into the model as:

$$ln(\mathrm{EFP_t}) = \beta_0 + \beta_1 ln(\mathrm{NEC_t}) + \beta_2 ln(\mathrm{REC_t}) + \pi_1(\mathrm{ERT_{t-1}}) + \pi_2(\mathrm{ERT_{t-2}}) + \pi_3(\mathrm{ERT_{t-3}}) + \pi_4(\mathrm{ERT_{t-4}}) + \mu_{it} \quad (6)$$

where:

$$\pi_j = \begin{cases} (j+1)\pi & 0 \le i \le k/2 \\ (k-i+1)\pi & k/2+1 \le i \le k \end{cases} \quad (7)$$

Furthermore, the environmental-related technologies variable dynamic procedure malformed the inverted-V lag distribution, as presented in Equation (7).

3.2. Empirical Methodology

This research scrutinizes the dynamic nexus between ecological footprint, nuclear energy, renewable energy, and environmental-related technologies in Pakistan. To test the integrated (unit root) order, the current research uses the Phillips Perron (PP) unit root test [53], augmented Dickey–Fuller (ADF) unit root test [54], and Zivot and Andrews' (ZA) unit root test [55] to verify the integration order. Moreover, to check the long-run cointegration association, this study further applied Gregory and Hansen's residual-based cointegration test [56]. In earlier studies, scholars applied linear methods to investigate the nexus between macroeconomics series. However, the major defect of linear approaches is that it does not have the full ability to discover the asymmetric effects. Additionally, data under deliberation for the present research may hold other intrinsic nonlinearities because of a longer time span. Therefore, the non-linear autoregressive distributive lag (NARDL) cointegration regression established by Shin et al. [57] is applied. The NARDL bound test has many advantageous features. First, the ARDL investigation can be applied even if the study series are free of unit root at the level. Second, this test allows all the testing variables to have diverse lags, which may be stationary at level I (0), first integrated order I (1), or mix integration order I (0,1), but it should not be second-order integrated I (2) [58]. Third, this test (NARDL) is free from the issue of spurious regression. Fourth, this test allows one to coalesce the cointegration and non-linear asymmetry in one equation.

Furthermore, this test inspects the positive and negative impacts of the decomposed variables on the explained series when the study regressors have negative and positive variations. Finally, in general, NARDL cointegration regression is a dynamic error correction (EC) representation, which estimates robust and reliable practical outcomes even in the presence of the micro-numerasticity (small sample) issue. Applying the NARDL test is feasible for both the negative and positive asymmetric long-run and short-run cointegration among the series. The asymmetric estimation equation for long-run [57] is reported in Equation (8) as:

$$lnEFP_t = \alpha_t + \gamma_t + \beta_1^+ ln(NEC_t^+) + \beta_2^- ln(NEC_t^-) + \beta_3^+ ln(REC_t^+) + \beta_4^- ln(REC_t^-) + \beta_5^+ ln(ZERT_t^+) + \beta_6^- ln(ZERT_t^-) + \varepsilon_t \quad (8)$$

where $lnEFP_t$ shows the explanation of the dependent variable, β_1^+, β_3^+, and β_5^+ are associated with long-run parameters, whereas β_2^-, β_4^-, and β_6^- are linked with negative parameters. In fact, NEC_t^+, REC_t^+, and $ZERT_t^+$ show the positive impacts in independent variables, while NEC_t^-, REC_t^-, and $ZERT_t^-$ denote the partial sum of negative impacts in the independent variable. For positive and negative impacts of nuclear energy, parameters are specifically presented in Equation (9) as:

$$\begin{cases} POS(lnNEC_t) = lnNEC_t^+ = \sum_{n=1}^{t} \Delta lnNEC_t^+ = \sum_{n=1}^{t} max(\Delta lnNEC_t^+, 0) \\ NEG(lnNEC_t) = lnNEC_t^- = \sum_{n=1}^{t} \Delta lnNEC_t^- = \sum_{n=1}^{t} min(\Delta lnNEC_t^+, 0) \end{cases} \quad (9)$$

For positive and negative impacts of renewable energy, parameters are specifically presented in Equation (10) as:

$$\begin{cases} POS(lnREC_t) = lnREC_t^+ = \sum_{n=1}^{t} \Delta lnREC_t^+ = \sum_{n=1}^{t} max(\Delta lnREC_t^+, 0) \\ NEG(lnREC_t) = lnREC_t^- = \sum_{n=1}^{t} \Delta lnREC_t^- = \sum_{n=1}^{t} min(\Delta lnREC_t^+, 0) \end{cases} \quad (10)$$

For positive and negative impacts of environmental-related technologies, parameters are specifically presented in Equation (9) as:

$$\begin{cases} POS(lnZERT_t) = lnZERT_t^+ = \sum_{n=1}^{t} \Delta lnZERT_t^+ = \sum_{n=1}^{t} max(\Delta lnZERT_t^+, 0) \\ NEG(lnZERT_t) = lnZERT_t^- = \sum_{n=1}^{t} \Delta lnZERT_t^- = \sum_{n=1}^{t} min(\Delta lnZERT_t^+, 0) \end{cases} \quad (11)$$

In the same way, consistent with Pesaran et al. (2001) and Shin et al. (2014), the NARDL formulation is presented in Equation (12) as:

$$\begin{aligned} \Delta lnEFP_t = \Psi_0 + & \sum_{i=1}^{n1} \pi_{1i} \Delta lnEFP_{t-i} + \sum_{i=0}^{n2} \pi_{2i} \Delta lnNEC_{t-1}^+ + \sum_{i=0}^{n3} \pi_{3i} \Delta lnNEC_t^- \\ & + \sum_{i=0}^{n3} \pi_{4i} \Delta lnREC_{t-1}^+ + \sum_{i=0}^{n5} \pi_{5i} \Delta lnREC_t^- + \sum_{i=0}^{n6} \pi_{6i} \Delta lnZERT_{t-1}^+ + \sum_{i=0}^{n7} \pi_{7i} \Delta lnZERT_t^- \\ & + \eta_1 lnEFP_{t-1} + \eta_2 lnNEC_{t-1}^+ + \eta_3 lnNEC_{t-1}^- + \eta_4 lnREC_{t-1}^+ + \eta_5 lnREC_{t-1}^- + \eta_6 lnZERT_{t-1}^+ \\ & + \eta_7 lnZERT_{t-1}^- + \varepsilon_t \end{aligned} \quad (12)$$

where Δ shows the change in the associated variable. The short-run asymmetric coefficient is denoted by $\pi_{1i} - \pi_{7i}$ and the long-run asymmetric coefficient is captured by $\eta_1 - \eta_7$. While $\sum_{i=0}^{n2} \pi_{2i} \Delta lnNEC_{t-1}^+$ and $\sum_{i=0}^{n3} \pi_{3i} \Delta lnNEC_t^-$ indicates the positive and negative impacts of NEC on EFP, $\sum_{i=0}^{n3} \pi_{4i} \Delta lnREC_{t-1}^+$ and $\sum_{i=0}^{n5} \pi_{5i} \Delta lnREC_t^-$ capture the short-run positive and negative impacts on EFP. Similarly, $\sum_{i=0}^{n6} \pi_{6i} \Delta lnZERT_{t-1}^+$ and $\sum_{i=0}^{n7} \pi_{7i} \Delta lnZERT_t^-$ indicate the positive and negative impacts on EFP. Moreover, n shows the optimal lag (determined by AIC) and ε denotes the stochastic error term. The verification of long-run cointegration association is explored by applying the bound procedure, which can be appropriate by comparing the critical value estimated through the F-statistic (Wald test), as proposed by Pesaran et al. [58] and Shin et al. [57].

4. Results and Discussion

4.1. Results of Descriptive Statistics and Correlation Matrix

Table 3 shows the descriptive statistics for all series incorporated in the current research. From this table, renewable energy consumption (REC) accounts for the highest mean (48.84400), median (47.96210), minimum (39.58050), and maximum (58.09129) in terms of magnitude values, followed by the environmental-related technologies (ERT) and nuclear energy consumption (NEC). In contrast, the ecological footprint has the lowest expected magnitude value, as it is noted that the ERT (6.862642) has a broader stretch as compared to REC (4.713678) and NEC (2.787288), while the least stretch variable is EFP (0.038000) in terms of standard deviation. Furthermore, all the selected time series variables are positively skewed. In contrast, the kurtosis magnitude values of all variables are not more than the adequate threshold (3), demonstrating a convergence from the series.

Table 3. Descriptive statistics of the study variables.

Stats. ↓	EFP	NEC	REC	ERT
Mean	0.774950	2.861441	48.84400	10.61390
Median	0.769267	2.317931	47.96210	9.997000
Maximum	0.855196	9.344590	58.09129	34.00000
Minimum	0.721552	0.079549	39.58050	1.740000
Std. Dev.	0.038000	2.787288	4.713678	6.862642
Skewness	0.443361	1.250832	0.004354	1.209785
Kurtosis	2.159690	2.553658	2.491649	2.357836
Jarque–Bera	1.927676	8.479612	0.333892	14.74271
Probability	0.381426	0.014410	0.846245	0.000629
Sum	24.02345	88.70468	1514.164	329.0310
Sum Sq. Dev.	0.043319	233.0693	666.5627	1412.876
Observations	31	31	31	31

On the other hand, the values estimated through the Jarque–Bera test of the NEC and ERT variables show that these series are not normally distributed. Consequently, the variations from normal distribution show the time-trending data behavior that rationalizes the NARDL application [59]. Moreover, Figure 2 shows the average trend analysis of the study variables (e.g., EFP, NEC, REC, and ERT).

After checking the descriptive statistics further, the present research checks the bivariate Pearson correlation matrix of the selected variables. To do this, Table 4 reveals the findings of the bivariate Pearson correlation matrix among the variables. The findings reveal that the log of NEC (LNEC) has a positive link with the log of EFP (LEFP), which is (0.46565). Conversely, the log of REC (LREC) and log of ZERT (LZERT) variables have an adverse correlation with LEFP. Specifically, LREC negatively linked with LEFP is (−0.61935), and between LZERT and LEFP is (−0.36571). Similarly, LNEC adversely correlates with LREC is (−0.62735). However, LZERT positively correlates with LNEC and LREC (0.42399 and 0.59357), respectively. Further, it confirms that none of the variables are very highly (0.85) correlated with another variable which confirms that there is no issue of multicollinearity.

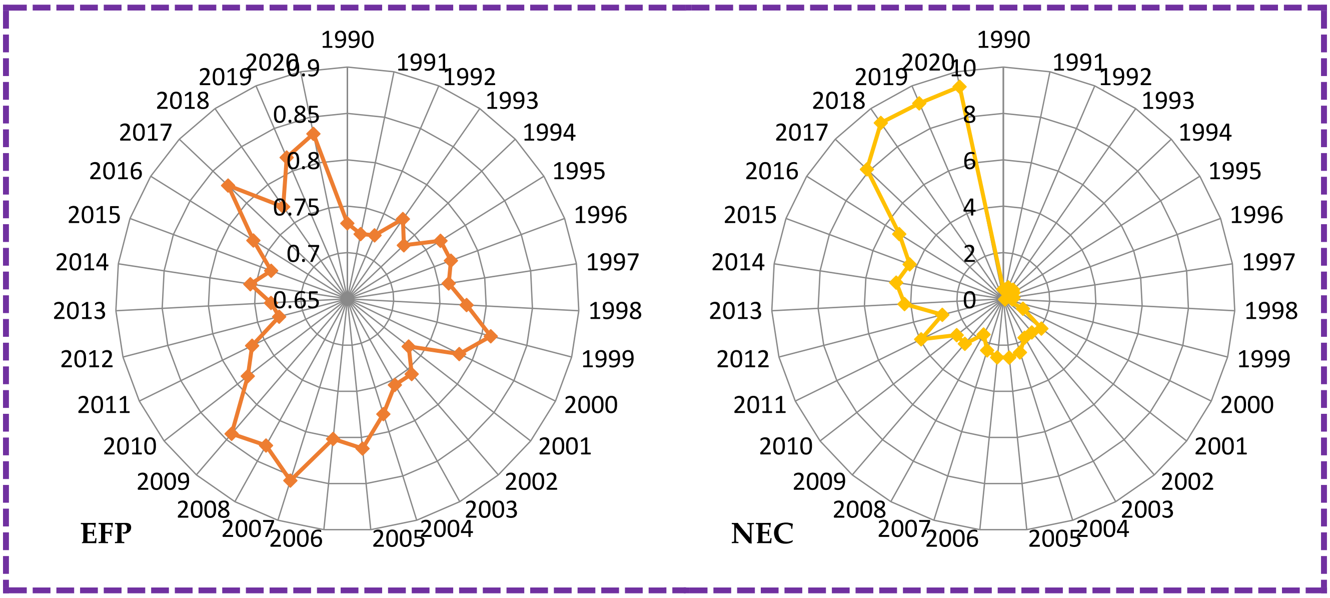

Figure 2. *Cont.*

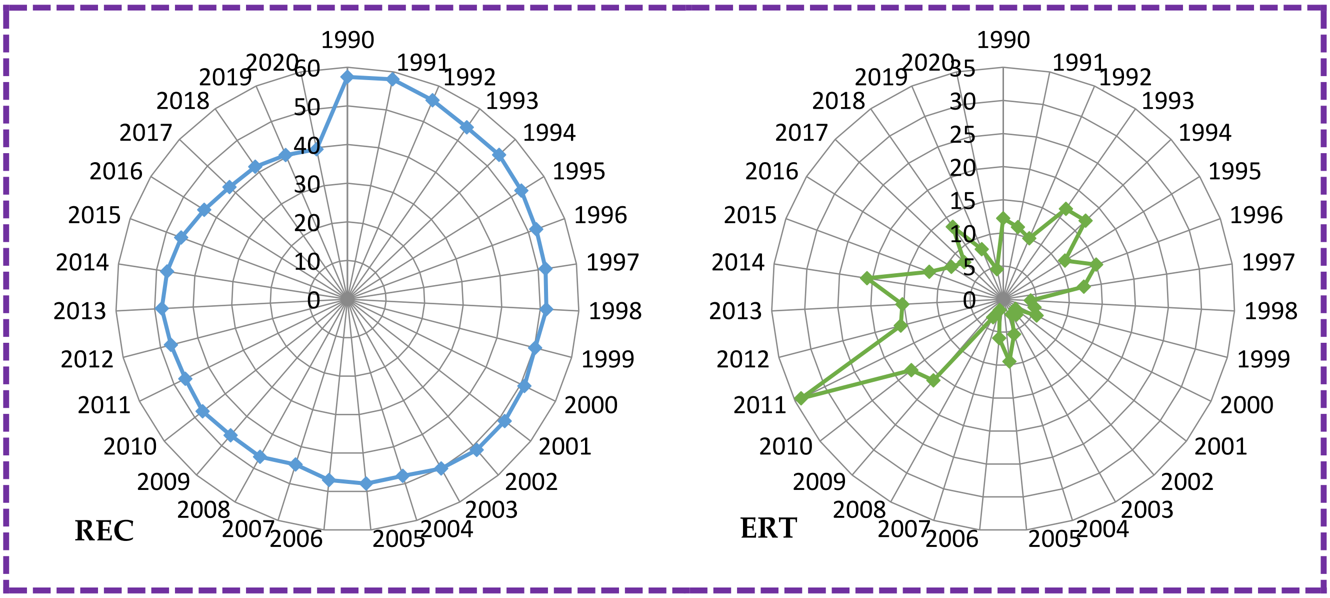

Figure 2. Average trend analysis of the study variables (e.g., EFP, NEC, REC, and ERT).

Table 4. Pearson correlation matrix.

Variables	LEFP	LNEC	LREC	LERT
LEFP	1.0000			
	——			
	——			
LNEC	0.46565 *	1.0000		
	[4.4838]	——		
	(0.0000)	——		
LREC	−0.61935 *	−0.62735 *	1.0000	
	[−4.2481]	[−6.9323]	——	
	(0.0002)	(0.0000)	——	
LZERT	−0.36571 *	0.42399 *	0.59357 *	1.0000
	[−2.1161]	[4.1292]	[5.1059]	——
	(0.0430)	(0.0000)	(0.0000)	——

Note: * shows 1% level of significance. The t-statistics are presented in [ ], and *p*-values are in ( ).

4.2. Results of Unit Root Tests (without and with Structural Break)

In the vein of linear ARDL and non-linear ARDL models, it is necessary that all the selected series should be either zero integrated order I(0), first integration order I(1), or a mix of integrated order I(0,1). For that reason, the current research initially checks the integration order of the series by employing ADF and PP unit root tests which are commonly identified as traditional unit root tests that have not been able to detect the structural breakpoint in the data set. Table 5 shows the empirical outcomes of both ADF and PP test information where these tests are applied at intercept and intercept and trend at the level I(0) and the first difference I(1). The null hypothesis (H0) under ADF and PP test statistics is that variables fall in the severe problem of a unit root. By applying the ADF unit root test, all the variables are non-stationary at the level in the case of intercept; nonetheless, LNEC and LZERT are stationary at a level in the case of intercept and trend. However, all the study variables turn to follow the stationary process at their first difference.

Table 5. ADF and PP unit root findings (without Structural Break).

Series ↓	Intercept				Intercept and Trend			
	Level		First Difference		Level		First Difference	
	t-Stats	Prob.	t-Stats	Prob.	t-Stats	Prob.	t-Stats	Prob.
				Augmented Dickey–Fuller (ADF)				
LEFP	−2.3218	0.1722	−6.5325 *	0.0000	−2.5419	0.3073	−6.4104 *	0.0002
LNEC	−1.2546	0.6370	−6.7926 *	0.0000	−3.6067 **	0.0462	−6.6743 *	0.0000
LREC	0.0233	0.9536	−4.9341 *	0.0004	−1.5852	0.7749	−4.8484 *	0.0028
LZERT	−2.2909	0.1829	−3.8836 *	0.0072	−3.4228 ***	0.0709	−3.9706 **	0.0244
				Phillips and Perron (PP)				
LEFP	−2.2954	0.1798	−6.5155 *	0.0000	−2.6617	0.2582	−6.3952 *	0.0001
LNEC	−1.1073	0.6997	−7.8308 *	0.0000	−3.6067 **	0.0462	−7.7041 *	0.0000
LREC	−0.0352	0.9478	−4.9518 *	0.0004	−1.8498	0.6551	−4.8689 *	0.0027
LZERT	−1.5260	0.5049	−5.2419 *	0.0000	−1.6186	0.7574	−4.8836 *	0.0009

Note: *, ** and *** show 1%, 5% and 10% level of significance.

Similarly, PP test statistics reveal that all the variables have unit root at the level of intercept, and only the LNEC variable is stationary at the level of intercept and trend. Conversely, the null hypothesis of the unit root is rejected at their first integrated order for all series which recommends that all the candidate variables are stationary at first integrated order I(1). Since there is a mixture of stationarity order, such as I(0,1), this allows us to use the NARDL method.

Further, the traditional time series unit root tests, for instance, ADF and PP and other conventional tests, habitually tend to biased and spurious outcomes by overlooking the structural break in the data series. This study performed Zivot and Andrews' (2002) unit root test to counter this issue, as reported in Table 6. The ZA unit root test findings signify the stationarity (no unit root) of the variables after pleasing the first integrated order providing dissimilar structural breaks in the series. This evenly reports the preference for a non-linear model that can strongly story for the influences of these economic ups and downs on the overall economic performance and offers consistent evaluations.

Table 6. Zivot and Andrews' unit root findings (with Structural Break).

Series ↓	Without Trend				With Trend			
	Level		First Difference		Level		First Difference	
	t-Stats	Break	t-Stats	Break	t-Stats	Break	t-Stats	Break
LEFP	−4.163	2010	−7.041 *	2014	−2.686	1996	−6.914 *	2013
LNEC	−3.691	2001	−8.025 *	2000	−3.758	1997	−5.689 *	2002
LREC	−2.361	2008	−6.341 *	2015	−2.603	2015	−5.697 *	2013
LZERT	−4.562	2010	−8.285 *	2016	−2.223	2001	−5.702 *	2012
Critical values	1%	5%	10%		1%	5%	10%	
	−5.34	−4.93	−4.58		−4.93	−4.42	−4.11	

Note: * shows 1% level of significance.

4.3. Results of Broock, Dechert, and Scheinkman (BDS) Test for Non-Linearity

In the selected data of the study variables, the authors applied the BDS independence test that was initially developed for nonlinearity discovery dependencies in the time series data by Broock et al. [60] in the presence of structural breaks. Table 7 provides the empirical findings of the BDS nonlinearity test, which explore the theory that that all study variables are not identically and independently distributed (iid). Therefore, the dynamic asymmetric skeleton is essential to confining non-linear relationships and structural shifts. Finally, after verifying the structural breaks and asymmetry in the series, the authors further move towards estimating the coefficients in the framework of the NARDL model.

Table 7. BDS test for nonlinearity.

Series →	**LEFP**	**LNEC**	**LREC**	**LZERT**
Dimension ↓	**BDS Statistic**	**BDS Statistic**	**BDS Statistic**	**BDS Statistic**
Dimension (2)	0.043440 *	0.126780 *	0.132519 *	0.149008 *
Dimension (3)	0.072549 *	0.205875 *	0.209808 *	0.237795 *
Dimension (4)	0.122108 *	0.247628 *	0.269916 *	0.276675 *
Dimension (5)	0.114545 *	0.265946 *	0.292631 *	0.277459 *
Dimension (6)	0.141157 *	0.270388 *	0.301010 *	0.249608 *

Note: * indicates the rejection of the null hypothesis of residuals of being (iid) at 1% significance level.

4.4. Cointegration Test Findings

After further testing the structural breaks and asymmetry in the selected data, it is essential to check the long-run cointegration relationship among series by applying the regime shift (structural break) cointegration test. To do this, we applied the Gregory–Hansen Test for long run cointegration with regime shifts. The finding of the Gregory–Hansen Test for cointegration with regime shifts is reported in Table 8. The null hypothesis is rejected due to the Z_t test statistics absolute vales (−8.18) being greater than asymptotic probability values at 5%, which is −5.28. Moreover, we observe that the break point date is 2006 in the study data set.

Table 8. Gregory–Hansen test for cointegration with regime shifts.

Tests	**Test Statistic**	**Breakpoint**	**Break Year**	**Asymptotic Critical Values**		
				1%	**5%**	**10%**
ADF	−8.02 *	17	2006	−5.77	−5.28	−5.02
Z_t	−8.18 *	17	2006	−5.77	−5.28	−5.02
Z_a	−38.79 *	17	2006	−63.64	−53.58	−48.65

Note: * shows 1% level of significance.

Further, this study employs another cointegration test name as the NARDL bound cointegration test. The findings of the NARDL bound cointegration test are reported in Table 9. It is noted from NARDL bound testing where the study found F-statistics when LEFP is considered as explained variables [F(LEFP) = (LNEC, LREC, and LZERT) = 8.145229], is higher than the lower as well as upper bound of the critical value at 1% significance level (I(0) Bound = 3.15, and I(1) Bound = 4.43). This result suggests that the null hypothesis of no cointegration can be rejected; relatively, we recognize the presence of a long-run association between LEFP, LNEC, LREC, and LZERT with positive and negative impacts in Pakistan. This supports the current research as it helps to define the significant presence of a long-run equilibrium relationship to which the variables converge over time.

Table 9. NARDL Bound Test.

Test Statistic	**Value**	**k**
F-statistic	8.145229	6
	Critical Value Bounds	
Significance	I(0) Bound	I(1) Bound
10%	2.12	3.23
5%	2.45	3.61
2.5%	2.75	3.99
1%	3.15	4.43

Null Hypothesis: No long-run associations exist.

4.5. Results of Nonlinear ARDL Estimates

The significant detection of the long-run relationship among study variables leads us to establish the influence of positive and negative impacts of nuclear energy, renewable energy, and environmental-related technologies on the ecological footprint in the short term as well as the long term. To express the long-term and short-term empirical results, the authors apply the NARDL estimation approach. The empirical results of the NARDL approach are expressed in Table 10. The estimated results explore an indirect long-run link between nuclear energy and the ecological footprint. Specifically, the positive impact of nuclear energy $\left(lnNEC_t^+\right)$ has an insignificant positive influence on the ecological footprint in the long-term. In contrast, the negative impact of nuclear energy use has a positive and statistically significant impact on the ecological footprint in the case of Pakistan. Particularly, a 1% negative augmentation impact of nuclear energy use $lnNEC_t^-$ will increase the environmental pollution by 0.0455% at a 5% significance level. This evidence shows that in the long run, nuclear energy will increase the emissions levels in Pakistan, which is analogous to the estimated results of Sadiq et al. [17] for the case of the BRICS region and the findings of Majeed et al. [61] for the case of Pakistan. Empirical results assert that Pakistan's nuclear operation produces almost no environmental pollution; shifting to nuclear energy could help to reduce emissions [17,18]. In this regard, the assortment of non-renewable energy supplies to renewable and cleaner energy is essential for Pakistan [61]. Despite the fact that nuclear power utilization is a high-emission energy resource, this type of electrical energy production requires a great deal of care regarding the safety and protection of substances. Nuclear power plant installation and radioactive waste management require being dealt with cautiously to avoid superfluous incidents/disasters that may have ecological and species health impacts [20]. As we discuss the power market shift from non-renewables to alternative and nuclear power, the findings certainly suggest that the operation of nuclear power plants does emit environmental pollution and does not have the ability to reduce greenhouse gas emissions. In view of the fact that nuclear power plants and reactors do discharge carbon dioxide through energy generation, they can be seen to be an alleviation technology in the long term for global warming and climate change [62]. Even if nuclear energy curbs pollution levels, it is imperative to note that nuclear reactors and power plants' tranquil pretence is in jeopardy due to their high dissimilarity in political, economic, and social indicators over the regions. These hazards ought to be cautiously diminished and considered when counting the ecological consequences and human health influences of nuclear energy generation [16,17].

In terms of log-run renewable energy analysis, the findings depict that the positive impact of renewable energy consumption has an unfavorable and statistically significant consequence on the ecological footprint. The coefficient/elasticity of the positive impact in renewable energy $lnREC_t^+$ (−0.2582%) is statistically significant at a 99% confidence interval, which means that positive impacts of renewable energy allow for a positive influence on environmental quality. On the other hand, a 1% boost in the adverse impacts of renewable energy $lnREC_t^-$ will increase the ecological footprint by (−1.2828%) in the long term by a 1% significance level. It shows that when the Pakistani policymakers and central authorities augment the consumption of renewable energy resources, environmental pollution tends to reduce and protect environmental excellence. The sign of the positive and negative impacts of the renewable energy coefficient are similar; however, their size of magnitude is widely diverged, which validates the nonlinearity/asymmetry between renewable energy and ecological footprint. This result is endorsed by Usman and Makhdum [6] for BRICS-T countries, Usman et al. [43] for 15 highly polluted countries, Khalid et al. [63] for SAARC countries, Usman and Balsalobre-Lorente [64] for newly industrialized countries, Balsalobre-Lorente et al. [65] for PIIGS region, and Usman et al. [66]. Consistent with the estimated findings and prior literature, these results confirm that those countries which transform their energy mode from fossil fuel to alternative or renewable energy resources have double payback on the economy and the environment [45,63,67]. Initially, producing energy in the course of renewable energy projects evades the option of fossil fuels and greenhouse gases and diminishes the probability of air contamination. After that, expanding the supply of their energy mix and exchange from imported fossil fuels and non-renewables also positively influences their country. As an emerging economy, the state of Pakistan has experienced air pollution and climate change issues over the previous two decades. In addition, it also faces many energy disasters that have a negative impact on its economy [68,69]. Over the last five years, the state of Pakistan also has taken some good steps and started many solar and wind energy ventures to increase the deployment of renewable energy and to reduce consumption of the fossil fuel energy resources that are considered the major sources of environmental pollution in an economy. While Pakistan targets several strategies and measures to address such problems, the power subdivision is not well-organized. The section of energy use from cleaner and renewable sources is very short; in the current system, it will take some time to assemble the set target.

Table 10. Findings of NARDL test [NARDL (1, 0, 0, 0, 0, 0, 1)].

Variable	Coefficient	Std. Error	t-Statistic	Prob.
		Long Run results		
LNEC_POS	0.002846	0.016179	0.175934	0.8626
LNEC_NEG	−0.045562 **	0.020076	−2.269412	0.0374
LREC_POS	−0.258250 *	0.058292	−4.430251	0.0006
LREC_NEG	−1.282881 *	0.242106	−5.298844	0.0001
LZERT_POS	−0.010954 *	0.003025	−3.620971	0.0023
LZERT_NEG	0.014123 ***	0.007592	1.860209	0.0813
C	−0.425000 *	0.046088	−9.221428	0.0000
		Short-run results		
D(LNEC_POS)	0.003043	0.017355	0.175363	0.8630
D(LNEC_NEG)	−0.048716 **	0.022672	−2.148736	0.0473
D(LREC_POS)	−0.062283	0.618435	−0.100710	0.9210
D(LREC_NEG)	−1.371694 *	0.327453	−4.188977	0.0007
D(LZERT_POS)	−0.011712 **	0.004259	−2.750141	0.0142
D(LZERT_NEG)	−0.023483 ***	0.013221	−1.776230	0.0947
CointEq. (−1)	−0.569229 *	0.179137	−3.177614	0.0001
R-squared	0.810601	Mean dependent var		−0.245006
Adjusted R-squared	0.715901	S.D. dependent var		0.046484
S.E. of regression	0.024777	Akaike info criterion		−4.284125
Sum squared resid	0.009822	Schwarz criterion		−3.845330
Log likelihood	62.55156	Hannan-Quinn criter.		−4.162422
F-statistic	8.559699	Durbin-Watson stat		2.351585
Prob(F-statistic)	0.000157			

Note: *, **, and *** show 1%, 5%, and 10% significance level, respectively.

In terms of the impact of environmental-related technologies on ecological footprint, this study shows that a positive impact in environmental-related technologies has an adverse influence on the ecological footprint. In particular, a 1% positive change in environmental-related technologies $lnZERT_t^+$ will lead to a decrease in environmental pollution by −0.0109% in the long run for Pakistan. Put oppositely, a 1% increase in the negative impact of environmental-related technologies $lnZERT_t^-$ will also reduce the overall pollution by (0.0141%) in Pakistan. The encouraging investment role in environmental-related technologies to curb the ecological footprint is observed in the estimated outcomes of the present research based on the state-of-the-art NARDL approach in the case of Pakistan's economy. This outcome is validated in several ways; for instance, Pakistan's economic exports are mostly based on the industrial sector that is now steadily shifting its technologies from conventional (non-renewable) to cleaner and modern (renewable) energy sources which will diminish the overall pollution level. Environmental-related technology development assists in overcoming fossil fuel energy utilization, and as a result, it minimizes energy deployment that will help to maintain sustainable development [23].

On the other hand, the adoption of environmental-related technologies is significantly associated with cleaner and alternative energy adoption and a decrease in the ecological footprint. Environmental-related technologies will promote green growth and work as an incentive for sustainable environmental performance in Pakistan. In this regard, considering the negative impact of environmental-related technology will increase the pollution level. These findings show that investments in environmental-related technologies are not well-organized by the government. Specifically, Pakistan should spotlight its investment pattern in environment-related technologies to overcome the pressure on the environment in terms of its ecological footprint. However, Pakistan's economy faces many challenges in the green economy due to it being short of cleaner, innovative technologies. The circular economy is further rethinking the process of industrialization; hence, it is more accentuated for the impact of innovations [70]. A circular economy is associated with the environment, economy, and society for sustainable growth. Technical alterations have the ability to play a noteworthy role in a green and circular economy. The United Nations Environment Protection (UNEP) summit report mentioned that a modern economy enhances the human species welfare by considerably diminishing pollution levels [71–74]. Furthermore, a graphical presentation of empirical findings is presented in Figure 3.

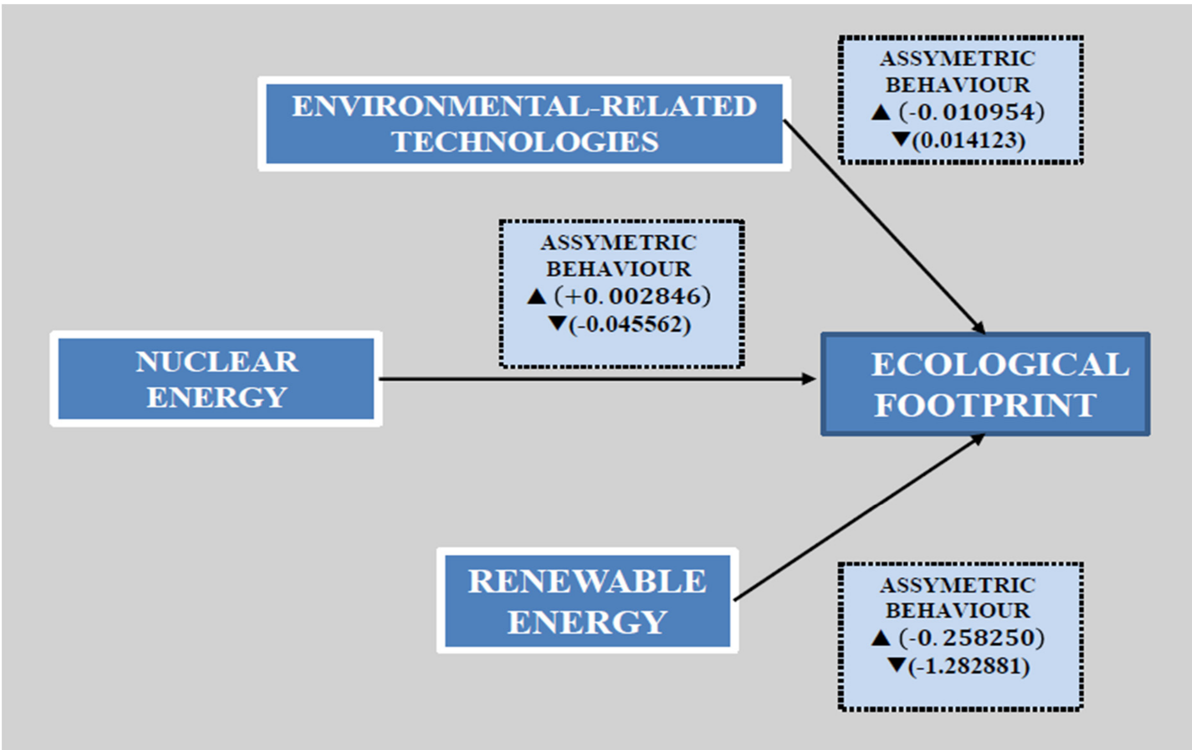

Figure 3. Graphical presentation of empirical findings.

Table 10 further reveals that the error correction term [CointEq. $(-1) = -0.569$] is significant and negative at 1% significance level. This shows that a stable equilibrium will occur (convergence/adjustment speed) from the short run to the long run in 1.756 years, which means Pakistan's economy is on the right track in renewable energy deployment. Therefore, this validates a long-run stable association running from nuclear energy, renewable energy, and environmental-related technologies to ecological footprint. Furthermore, the p-value of the F-test statistic is statistically significant at the 99% confidence interval level, which shows that the F-statistic (8.5596) is sufficiently outsized to elucidate the overall regressors significance. The approximation has a largely important expounding power, providing a high value (0.8106) of R-square. The explanatory variables (NEC, REC, and ZERT) explain an 81% deviation in the explained variable, such as the ecological footprint.

Furthermore, each test of heteroscedasticity, serial correlation, and model specification is not significant, which proves the nonexistence of any issue mentioned above and is a good fit for the model. The Durbin–Watson value (2.3515) is also lowered to 2.5, demonstrating that our model is following the free of serial correlation issue.

The present research used the dynamic multiplier graphs to test the nonlinearity/asymmetry owing to negative and positive impacts in ecological footprint. As presented in Figures 4–6, the multiplier curves recommend the findings of nonlinearity adjustment of ecological footprint to its negative and positive impacts in the stable long-run equilibrium. These multiplier graphs also reveal that the negative nuclear energy, renewable energy, and environmental-related technologies impacts have more influence on ecological footprint than positive impacts in the specified model for the long run.

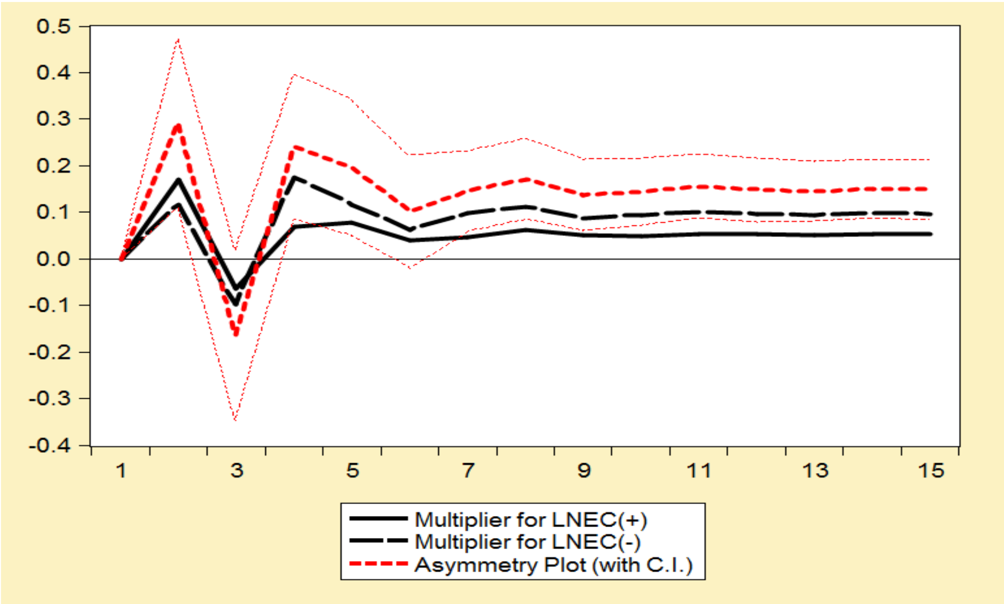

Figure 4. Dynamic Multiplier graph for LNEC.

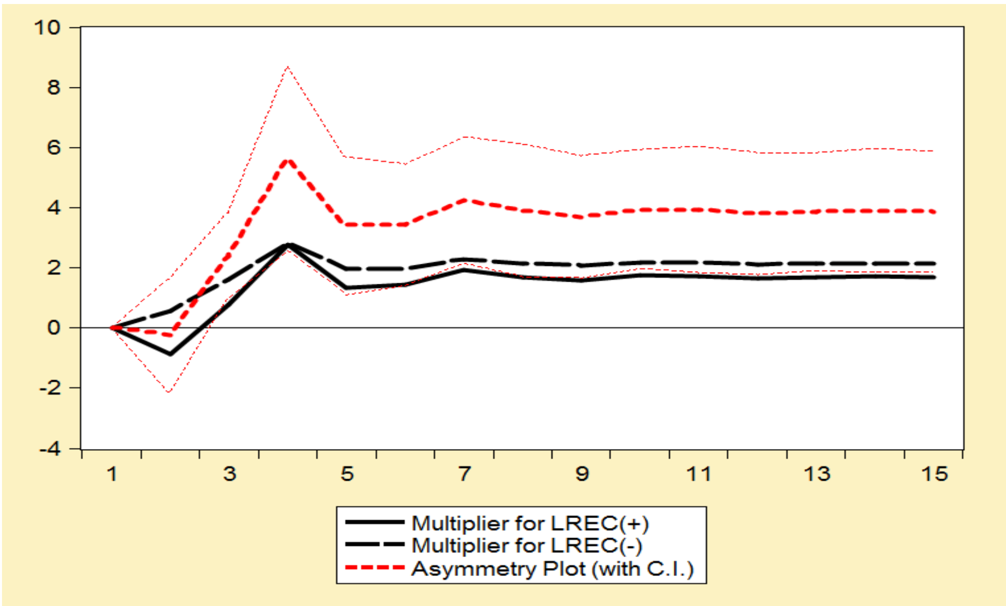

Figure 5. Dynamic Multiplier graph for LREC.

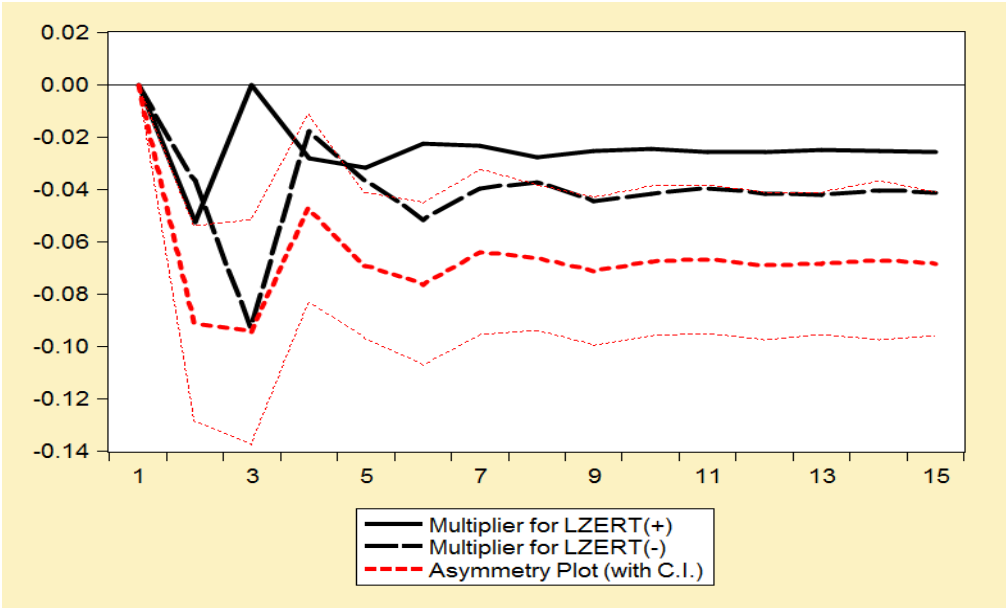

Figure 6. Dynamic Multiplier graph for LZERT.

4.6. Sensitivity Analysis

Table 11 provides detailed information about the reliability/sensitivity tests of the study model. According to the findings of Table 11, the ARCH and Brush–Pagan–Godfrey tests show the study model is free of the heteroscedasticity issue, which verifies that the error term of the model follows the homogeneous distribution. Moreover, the finding of the Breusch–Godfrey LM tests reveals that our model is also free of autocorrelation setbacks. Furthermore, the F-statistics and *p*-value of the Jarque–Bera normality test verifies that the data is perfectly normally distributed. At the same time, the Ramsey RESET test for model specification shows that the study model is well specified for our estimation.

Table 11. Some sensitivity analysis.

Tests	F-Statistic	Prob.
ARCH test for Heteroskedasticity	0.307293	0.5852
Breusch–Pagan–Godfrey test for Heteroskedasticity	0.976755	0.5969
Breusch–Godfrey LM Test for Autocorrelation	0.727969	0.4834
Jarque–Bera for Normality	0.594470	0.7428
Ramsey RESET test for Model Specification	1.410686	0.2534

The NARDL model stability is checked in CUSUM and CSUSMQ tests. The findings of these tests are expressed in Figures 7 and 8. These figures reveal that the models are stable as the anticipated line is within the boundaries of the critical line at a 5% level of significance.

4.7. Testing Asymmetry in the Series

Table 12 reports the outcomes of the Wald test for the determination of both long-run and short-run asymmetries. To do this, we performed the WALD test of asymmetries. The empirical results of this test further verified the long-run asymmetric/nonlinear association between nuclear energy, renewable energy, environmental-related technologies, and ecological footprint. Similarly, except for renewable energy, all other series verify the asymmetric association in the context of Pakistan.

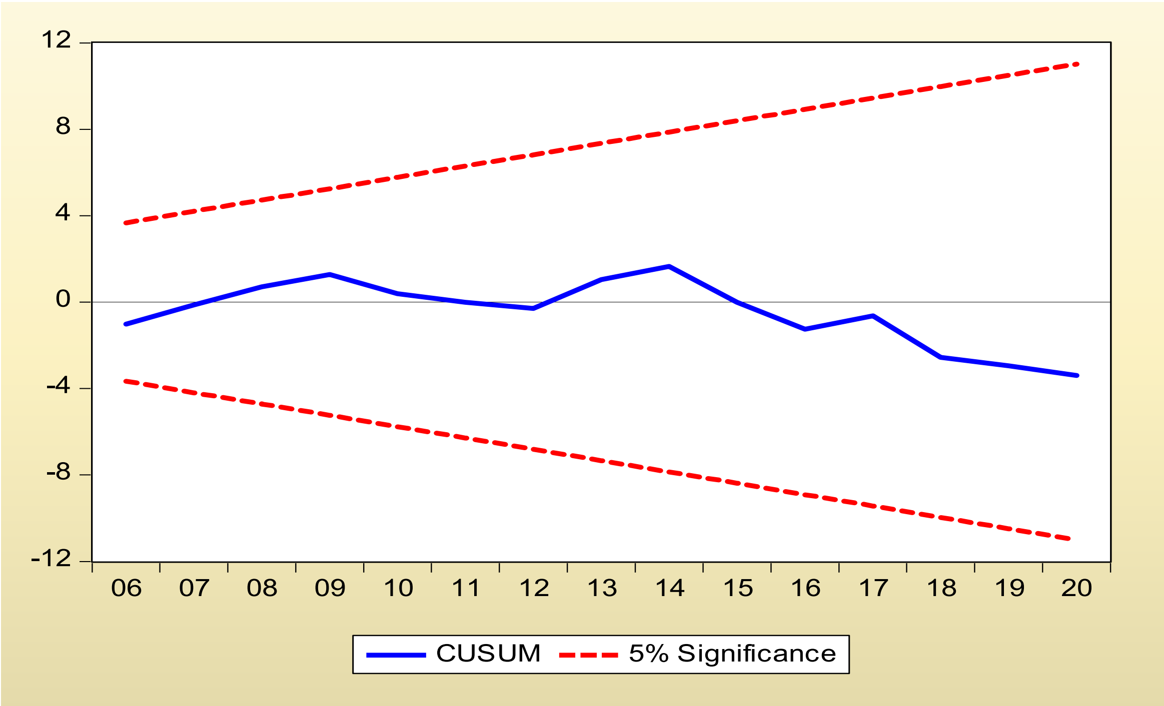

Figure 7. NARDL-CUSUM test graph.

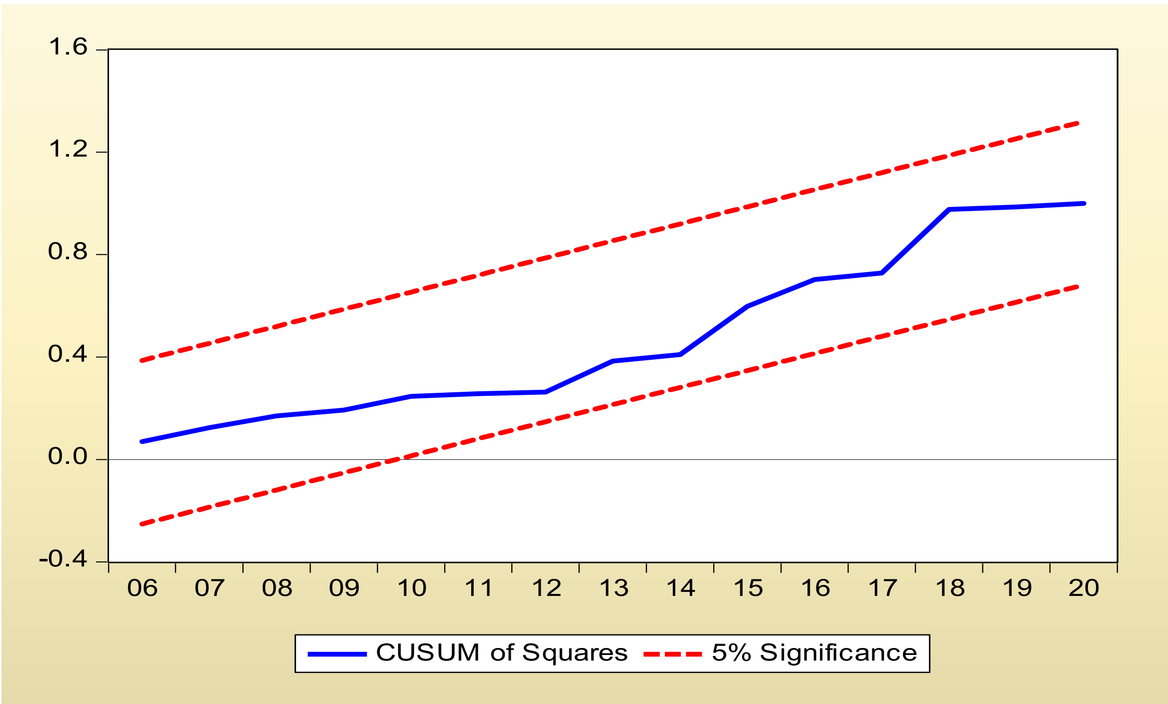

Figure 8. NARDL-CUSUM of square.

Table 12. Test to check long-run asymmetries.

Variables	F-Statistic	Prob.	Decision
Long-run asymmetry findings			
Nuclear energy consumption	31.60802 **	0.0302	Significant asymmetric relationship
Renewable energy consumption	51.32221 **	0.0189	Significant asymmetric relationship
Environmental related technologies	26.11786 **	0.0362	Significant asymmetric relationship
Short-run asymmetry findings			
Nuclear energy consumption	13.69939 ***	0.0659	Significant asymmetric relationship
Renewable energy consumption	2.065317	0.2872	No significant asymmetric relationship
Environmental related technologies	73.25439 **	0.0134	Significant asymmetric relationship

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

5. Conclusions and Policy Suggestions

The major aim of this research was to test the non-linear relation between renewable energy, nuclear energy, and environmental-related technologies on the ecological footprint in Pakistan from 1990 to 2020. Previous studies have focused on Pakistan, which has tested the linear relationship between those variables or used CO_2 emissions as the dependent variable. The authors have also tested the dynamic process in the V-finite lag distribution structure framework for environmental-related technologies. We applied ADF PP, and Zivot and Andrews' unit root tests with structural breaks. After that, the authors used the BDS test to check nonlinearity and asymmetry. The Gregory–Hansen test with regime shifts and NARDL bound cointegration tests were used to test the cointegration of these selected variables in the long run. A NARDL was performed to check the short-run and long-run relations between those candidate variables and ecological footprint and sensitivity analysis for checking the error autocorrelation and heteroskedasticity based on Breusch–Pagan–Godfrey and Arch tests or if the model is well specified using the Ramsey Reset test.

The findings showed that variables are integrated in a different order. The asymmetry was validated so that the NARDL model is suitable for checking the short-run and long-run relation between those regressors and ecological footprint. The results of NARDL estimations show that negative impacts in nuclear energy, renewable energy, and environmental-related technologies have more influence on ecological footprints than positive impacts both in the long-term and short-term. These results are explained by the fact that innovation is related to promoting alternative clean energy sources that reduce pollution. The results of the Wald test show that all explanatory variables display asymmetric relationships to the ecological footprint in the long-run and short-run, except renewable energy, which displays an insignificant asymmetric relationship with an ecological footprint in the short-run.

So, in Pakistan, the focus should be on supporting the innovation process to promote clean and alternative energy sources to cope with the ongoing industrialization process and the significant growth of the population. There is also the need for investments in research to make nuclear energy a clean energy source because Pakistan can broadly use this type of energy for economic activity. Pakistan faces many challenges such as energy crisis, energy efficiency, and significant environmental problems that need to be addressed immediately. At the same time, Pakistan represents a significant nuclear power globally; to use its nuclear energy, a common pollutant energy source, substantial investments are needed to achieve the necessary infrastructure. In any case, generating nuclear power requires safety measures and regulatory institutions to strictly monitor this process. Energy sector coordination must be improved at the governmental level. Pakistan should support investments into renewable energy source projects, such as wind and solar power, as well as its ongoing hydropower projects, to diminish its reliance on fossil-fuel energy sources such as coal, oil, and gas that highly and negatively impact the environment.

This research for Pakistan can be enlarged by adding a few more explanatory variables that are significant for this economy, such as population growth, globalization, and FDI inflows, in order to check their impact on the ecological footprint.

Author Contributions: M.U.: conceptualization, data curation, software, methodology, formal analysis, writing—original draft; A.J.: investigation, writing—original draft; M.R.: supervision, visualization, writing—original draft; D.B.-L.: project administration, writing—original draft, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Datasets are available at the links mentioned into the text.

Conflicts of Interest: Authors declare no conflict of interests.

Abbreviations

NEC—nuclear energy, EC—economic complexity, CO_2—carbon emission, TRD—trade openness, GDP—economic growth, URB—urbanization, TECH—technological innovation, ARDL—augmented autoregressive distributed lag, AMG—Augmented Mean Group, EFP—ecological footprint, FD—financial development, AGR—agricultural value added, OECD—Organization for Economic Co-operation and Development, GLO—globalization, NR—natural resources, FMOLS—Full Modified Ordinary Least Square, DOLS—Dynamic Ordinary Least Square, ARDL—Autoregressive Distributed Lag, TOU—tourism, INC—income per capita, NREC—Non-renewable energy consumption, REC—renewable energy consumption, HC—human capital index, MARS—Multivariate adaptive regression splines, MCVAR—Multivariate cointegrated vector auto regression, CUP-FM—Continuously Updated Fully Modified, CUP-BC—Continuously Updated Bias-Corrected, D-K—Driscoll–Kraay regression, NARDL—non-linear autoregressive distributed lag, PMG—pooled mean group, DSUR—dynamic seemingly unrelated regression, PLFCM—Partially linear functional-coefficient models, MMQR—Methods of Moments-Quantile-Regression, BENG—biomass energy use, GCF—gross capital formation, and FR—forestry.

References

1. Yang, B.; Usman, M.; Jahanger, A. Do industrialization, economic growth and globalization processes influence the ecological footprint and healthcare expenditures? Fresh insights based on the STIRPAT model for countries with the highest healthcare expenditures. *Sustain. Prod. Consum.* **2021**, *28*, 893–910. [CrossRef]
2. IEA. Global Energy Review 2021. Available online: https://www.iea.org/reports/global-energy-review-2021 (accessed on 15 February 2022).
3. Kamal, M.; Usman, M.; Jahanger, A.; Balsalobre-Lorente, D. Revisiting the Role of Fiscal Policy, Financial Development, and Foreign Direct Investment in Reducing Environmental Pollution during Globalization Mode: Evidence from Linear and Nonlinear Panel Data Approaches. *Energies* **2021**, *14*, 6968. [CrossRef]
4. Usman, M.; Kousar, R.; Makhdum, M.S.A.; Yaseen, M.R.; Nadeem, A.M. Do financial development, economic growth, energy consumption, and trade openness contribute to increase carbon emission in Pakistan? An insight based on ARDL bound testing approach. *Environ. Dev. Sustain.* **2022**, 1–30. [CrossRef]
5. Yang, B.; Jahanger, A.; Usman, M.; Khan, M.A. The dynamic linkage between globalization, financial development, energy utilization, and environmental sustainability in GCC countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 16568–16588. [CrossRef]
6. Usman, M.; Makhdum, M.S.A. What abates ecological footprint in BRICS-T region? Exploring the influence of renewable energy, non-renewable energy, agriculture, forest area and financial development. *Renew. Energy* **2021**, *179*, 12–28. [CrossRef]
7. Usman, M.; Khalid, K.; Mehdi, M.A. What determines environmental deficit in Asia? Embossing the role of renewable and non-renewable energy utilization. *Renew. Energy* **2021**, *168*, 1165–1176. [CrossRef]
8. Ramzan, M.; Raza, S.A.; Usman, M.; Sharma, G.D.; Iqbal, H.A. Environmental cost of non-renewable energy and economic progress: Do ICT and financial development mitigate some burden? *J. Clean. Prod.* **2021**, *333*, 130066. [CrossRef]

9. Jahanger, A.; Usman, M.; Murshed, M.; Mahmood, H.; Balsalobre-Lorente, D. The linkages between natural resources, human capital, globalization, economic growth, financial development, and ecological footprint: The moderating role of technological innovations. *Resour. Policy* **2022**, *76*, 102569. [CrossRef]
10. Ahmad, U.S.; Usman, M.; Hussain, S.; Jahanger, A.; Abrar, M. Determinants of renewable energy sources in Pakistan: An overview. *Environ. Sci. Pollut. Res.* **2022**, *29*, 29183–29201. [CrossRef]
11. WDI. World Bank (World Development Indicators). Available online: https://databank.worldbank.org/source/world-development-indicators# (accessed on 14 March 2022).
12. Jahanger, A.; Usman, M.; Ahmad, P. A step towards sustainable path: The effect of globalization on China's carbon productivity from panel threshold approach. *Environ. Sci. Pollut. Res.* **2021**, *29*, 8353–8368. [CrossRef]
13. Dagar, V.; Khan, M.K.; Alvarado, R.; Usman, M.; Zakari, A.; Rehman, A.; Murshed, M.; Tillaguango, B. Variations in technical efficiency of farmers with distinct land size across agro-climatic zones: Evidence from India. *J. Clean. Prod.* **2021**, *315*, 128109. [CrossRef]
14. Usman, M.; Balsalobre-Lorente, D.; Jahanger, A.; Ahmad, P. Pollution concern during globalization mode in financially resource-rich countries: Do financial development, natural resources, and renewable energy consumption matter? *Renew. Energy* **2022**, *183*, 90–102. [CrossRef]
15. NEI, Statistics 2018. Available online: https://www.nei.org/resources/statistics (accessed on 15 February 2022).
16. Qader, M.R.; Khan, S.; Kamal, M.; Usman, M.; Haseeb, M. Forecasting carbon emissions due to electricity power generation in Bahrain. *Environ. Sci. Pollut. Res.* **2021**, *29*, 17346–17357. [CrossRef] [PubMed]
17. Sadiq, M.; Shinwari, R.; Usman, M.; Ozturk, I.; Maghyereh, A.I. Linking nuclear energy, human development and carbon emission in BRICS region: Do external debt and financial globalization protect the environment? *Nucl. Eng. Technol.* **2022**, *in press*. [CrossRef]
18. Baek, J. Do nuclear and renewable energy improve the environment? Empirical evidence from the United States. *Ecol. Indic.* **2016**, *66*, 352–356. [CrossRef]
19. Bandyopadhyay, A.; Rej, S. Can nuclear energy fuel an environmentally sustainable economic growth? Revisiting the EKC hypothesis for India. *Environ. Sci. Pollut. Res.* **2021**, *28*, 63065–63086. [CrossRef]
20. Lau, L.-S.; Choong, C.-K.; Ng, C.-F.; Liew, F.-M.; Ching, S.-L. Is nuclear energy clean? Revisit of Environmental Kuznets Curve hypothesis in OECD countries. *Econ. Model.* **2019**, *77*, 12–20. [CrossRef]
21. Mahmood, N.; Danish; Wang, Z.; Zhang, B. The role of nuclear energy in the correction of environmental pollution: Evidence from Pakistan. *Nucl. Eng. Technol.* **2020**, *52*, 1327–1333. [CrossRef]
22. Wang, Z.; Danish; Zhang, B.; Wang, B. Renewable energy consumption, economic growth and human development index in Pakistan: Evidence form simultaneous equation model. *J. Clean. Prod.* **2018**, *184*, 1081–1090. [CrossRef]
23. Usman, M.; Hammar, N. Dynamic relationship between technological innovations, financial development, renewable energy, and ecological footprint: Fresh insights based on the STIRPAT model for Asia Pacific Economic Cooperation countries. *Environ. Sci. Pollut. Res.* **2021**, *28*, 15519–15536. [CrossRef]
24. Rahman, M.M.; Alam, K.; Velayutham, E. Reduction of CO_2 emissions: The role of renewable energy, technological innovation and export quality. *Energy Rep.* **2022**, *8*, 2793–2805. [CrossRef]
25. Zhang, F. *In the Dark: How Much Do Power Sector Distortions Cost South Asia?* World Bank Publications: Washington, DC, USA, 2018. Available online: https://openknowledge.worldbank.org/bitstream/handle/10986/30923/9781464811548.pdf?sequence=8 (accessed on 10 March 2022).
26. IEP. Pakistan Energy Demand Forecast (2021–2030) Report. 2021. Available online: https://www.pc.gov.pk/uploads/report/IEP_Report_FINAL.pdf (accessed on 24 March 2022).
27. Usman, M.; Jahanger, A.; Makhdum, M.S.A.; Balsalobre-Lorente, D.; Bashir, A. How do financial development, energy consumption, natural resources, and globalization affect Arctic countries' economic growth and environmental quality? An advanced panel data simulation. *Energy* **2021**, *241*, 122515. [CrossRef]
28. Hassan, S.T.; Danish; Khan, S.-U.D.; Baloch, M.A.; Tarar, Z.H. Is nuclear energy a better alternative for mitigating CO_2 emissions in BRICS countries? An empirical analysis. *Nucl. Eng. Technol.* **2020**, *52*, 2969–2974. [CrossRef]
29. Hassan, S.T.; Khan, D.; Zhu, B.; Batool, B. Is public service transportation increase environmental contamination in China? The role of nuclear energy consumption and technological change. *Energy* **2022**, *238*, 121890. [CrossRef]
30. Kartal, M.T. The role of consumption of energy, fossil sources, nuclear energy, and renewable energy on environmental degradation in top-five carbon producing countries. *Renew. Energy* **2022**, *184*, 871–880. [CrossRef]
31. Rehman, A.; Ma, H.; Ozturk, I.; Radulescu, M. Revealing the dynamic effects of fossil fuel energy, nuclear energy, renewable energy, and carbon emissions on Pakistan's economic growth. *Environ. Sci. Pollut. Res.* **2022**, 1–11. [CrossRef] [PubMed]
32. Saidi, K.; Omri, A. Reducing CO_2 emissions in OECD countries: Do renewable and nuclear energy matter? *Prog. Nucl. Energy* **2020**, *126*, 103425. [CrossRef]
33. Baek, J.; Pride, D. On the income–nuclear energy–CO_2 emissions nexus revisited. *Energy Econ.* **2014**, *43*, 6–10. [CrossRef]
34. Danish; Ulucak, R.; Erdogan, S. The effect of nuclear energy on the environment in the context of globalization: Consumption vs. production-based CO_2 emissions. *Nucl. Eng. Technol.* **2021**, *54*, 1312–1320. [CrossRef]
35. Usman, A.; Ullah, S.; Ozturk, I.; Chishti, M.Z.; Zafar, S.M. Analysis of asymmetries in the nexus among clean energy and environmental quality in Pakistan. *Environ. Sci. Pollut. Res.* **2020**, *27*, 20736–20747. [CrossRef]

36. Sarkodie, S.A.; Adams, S. Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa. *Sci. Total Environ.* **2018**, *643*, 1590–1601. [CrossRef] [PubMed]
37. Bilal, A.; Li, X.; Zhu, N.; Sharma, R.; Jahanger, A. Green Technology Innovation, Globalization, and CO_2 Emissions: Recent Insights from the OBOR Economies. *Sustainability* **2022**, *14*, 236. [CrossRef]
38. Lin, B.; Ma, R. Green technology innovations, urban innovation environment and CO_2 emission reduction in China: Fresh evidence from a partially linear functional-coefficient panel model. *Technol. Forecast. Soc. Change* **2022**, *176*, 121434. [CrossRef]
39. Yang, B.; Jahanger, A.; Ali, M. Remittance inflows affect the ecological footprint in BICS countries: Do technological innovation and financial development matter? *Environ. Sci. Pollut. Res.* **2021**, *28*, 23482–23500. [CrossRef]
40. Cheng, C.; Ren, X.; Wang, Z. The impact of renewable energy and innovation on carbon emission: An empirical analysis for OECD countries. *Energy Procedia* **2019**, *158*, 3506–3512. [CrossRef]
41. Chen, Y.; Lee, C.-C. Does technological innovation reduce CO_2 emissions?Cross-country evidence. *J. Clean. Prod.* **2020**, *263*, 121550. [CrossRef]
42. Dogan, E.; Ozturk, I. The influence of renewable and non-renewable energy consumption and real income on CO_2 emissions in the USA: Evidence from structural break tests. *Environ. Sci. Pollut. Res.* **2017**, *24*, 10846–10854. [CrossRef]
43. Usman, M.; Makhdum, M.S.A.; Kousar, R. Does financial inclusion, renewable and non-renewable energy utilization accelerate ecological footprints and economic growth? Fresh evidence from 15 highest emitting countries. *Sustain. Cities Soc.* **2021**, *65*, 102590. [CrossRef]
44. Dong, K.; Sun, R.; Jiang, H.; Zeng, X. CO_2 emissions, economic growth, and the environmental Kuznets curve in China: What roles can nuclear energy and renewable energy play? *J. Clean. Prod.* **2018**, *196*, 51–63. [CrossRef]
45. Huang, Y.; Haseeb, M.; Usman, M.; Ozturk, I. Dynamic association between ICT, renewable energy, economic complexity and ecological footprint: Is there any difference between E-7 (developing) and G-7 (developed) countries? *Technol. Soc.* **2022**, *68*, 101853. [CrossRef]
46. Wan, X.; Jahanger, A.; Usman, M.; Radulescu, M.; Balsalobre-Lorente, D.; Yu, Y. Exploring the Effects of Economic Complexity and the Transition to a Clean Energy Pattern on Ecological Footprint From the Indian Perspective. *Front. Environ. Sci.* **2022**, *9*, 1–17. [CrossRef]
47. Usman, M.; Anwar, S.; Yaseen, M.R.; Makhdum, M.S.A.; Kousar, R.; Jahanger, A. Unveiling the dynamic relationship between agriculture value addition, energy utilization, tourism and environmental degradation in South Asia. *J. Public Aff.* **2021**, e2712. [CrossRef]
48. GFPN. Global Footprint Network. Available online: https://www.footprintnetwork.org/our-work/ecological-footprint (accessed on 14 March 2022).
49. BP (British Petroleum). Statistical Review of World Nuclear Energy. BP Database. Available online: https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/nuclear-energy.html (accessed on 14 March 2022).
50. WB. World Development Indicators. (Online). Available online: https://databank.worldbank.org/source/world-developmentindicators (accessed on 25 December 2021).
51. OECD. OECD Stat. *Environmental-Related Statistics Technologies Development of Environment-Related Technologies, % All Technologies*. Available online: https://stats.oecd.org/Index.aspx?DataSetCode=PAT_IND# (accessed on 14 March 2022).
52. De Leeuw, F. The Demand for Capital Goods by Manufacturers: A Study of Quarterly Time Series. *Econometrica* **1962**, *30*, 407. [CrossRef]
53. Phillips, P.C.B.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
54. Dickey, D.A.; Fuller, W.A. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *J. Am. Stat. Assoc.* **1979**, *74*, 427–431. [CrossRef]
55. Zivot, E.; Andrews, D.W.K. Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis. *J. Bus. Econ. Stat.* **2002**, *20*, 25–44. [CrossRef]
56. Gregory, A.W.; Hansen, B.E. Residual-based tests for cointegration in models with regime shifts. *J. Econ.* **1996**, *70*, 99–126. [CrossRef]
57. Shin, Y.; Yu, B.; Greenwood-Nimmo, M. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. In *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*; Sickles, R.C., Horrace, W.C., Eds.; Springer: New York, NY, USA, 2014; pp. 281–314.
58. Pesaran, M.H.; Shin, Y.; Smith, R.J. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econom.* **2001**, *16*, 289–326. [CrossRef]
59. Hashmi, S.M.; Chang, B.H.; Shahbaz, M. Asymmetric effect of exchange rate volatility on India's cross-border trade: Evidence from global financial crisis and multiple threshold nonlinear autoregressive distributed lag model. *Aust. Econ. Pap.* **2021**, *60*, 64–97. [CrossRef]
60. Broock, W.A.; Scheinkman, J.A.; Dechert, W.D.; LeBaron, B. A test for independence based on the correlation dimension. *Econ. Rev.* **1996**, *15*, 197–235. [CrossRef]
61. Majeed, M.T.; Ozturk, I.; Samreen, I.; Luni, T. Evaluating the asymmetric effects of nuclear energy on carbon emissions in Pakistan. *Nucl. Eng. Technol.* **2021**, *54*, 1664–1673. [CrossRef]
62. IAEA. Nuclear Power and the Paris Agreement. International Atomic Energy Agency (IAEA), Vienna. Available online: https://www.iaea.org/node/41617 (accessed on 25 March 2022).

63. Khalid, K.; Usman, M.; Mehdi, M.A. The determinants of environmental quality in the SAARC region: A spatial heterogeneous panel data approach. *Environ. Sci. Pollut. Res.* **2021**, *28*, 6422–6436. [CrossRef] [PubMed]
64. Usman, M.; Balsalobre-Lorente, D. Environmental concern in the era of industrialization: Can financial development, renewable energy and natural resources alleviate some load? *Energy Policy* **2022**, *162*, 112780. [CrossRef]
65. Balsalobre-Lorente, D.; Ibáñez-Luzón, L.; Usman, M.; Shahbaz, M. The environmental Kuznets curve, based on the economic complexity, and the pollution haven hypothesis in PIIGS countries. *Renew. Energy* **2022**, *185*, 1441–1455. [CrossRef]
66. Usman, M.; Kousar, R.; Yaseen, M.R.; Makhdum, M.S.A. An empirical nexus between economic growth, energy utilization, trade policy, and ecological footprint: A continent-wise comparison in upper-middle-income countries. *Environ. Sci. Pollut. Res.* **2020**, *27*, 38995–39018. [CrossRef]
67. Jahanger, A.; Usman, M.; Balsalobre-Lorente, D. Autocracy, democracy, globalization, and environmental pollution in developing world: Fresh evidence from STIRPAT model. *J. Public Aff.* **2021**, e2753. [CrossRef]
68. Komal, R.; Abbas, F. Linking financial development, economic growth and energy consumption in Pakistan. *Renew. Sustain. Energy Rev.* **2015**, *44*, 211–220. [CrossRef]
69. Usman, M.; Kousar, R.; Makhdum, M.S.A. The role of financial development, tourism, and energy utilization in environmental deficit: Evidence from 20 highest emitting economies. *Environ. Sci. Pollut. Res.* **2020**, *27*, 42980–42995. [CrossRef]
70. Rosa, P.; Sassanelli, C.; Urbinati, A.; Chiaroni, D.; Terzi, S. Assessing relations between Circular Economy and Industry 4.0: A systematic literature review. *Int. J. Prod. Res.* **2020**, *58*, 1662–1687. [CrossRef]
71. UNEP. Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication—A Synthesis for Policy Makers. Available online: www.unep.org/greeneconomy. (accessed on 20 March 2022).
72. Usman, M.; Jahanger, A. Heterogeneous effects of remittances and institutional quality in reducing environmental deficit in the presence of EKC hypothesis: A global study with the application of panel quantile regression. *Environ. Sci. Pollut. Res.* **2021**, *28*, 37292–37310. [CrossRef]
73. Ramzan, M.; Iqbal, H.A.; Usman, M.; Ozturk, I. Environmental pollution and agricultural productivity in Pakistan: New insights from ARDL and wavelet coherence approaches. *Environ. Sci. Pollut. Res.* **2022**, *29*, 28749–28768. [CrossRef] [PubMed]
74. Intisar, R.A.; Yaseen, M.R.; Kousar, R.; Usman, M.; Makhdum, M.S.A. Impact of Trade Openness and Human Capital on Economic Growth: A Comparative Investigation of Asian Countries. *Sustainability* **2020**, *12*, 2930. [CrossRef]