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The Impact of Nuclear Energy Consumption, Green Technological Innovation, and Trade Openness on the Sustainable Environment in the USA

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Abstract: Nuclear energy, renewable energy, and alternative energy sources are all crucial for sustainable green energy. However, the existing literature often needs to pay more attention to the role of nuclear energy in achieving sustainable development goals. This study analyzes the impact of green technological innovation, nuclear energy consumption, and trade openness on environmental quality in the US. The authors used the ARDL bounds to identify cointegration relationships, which is appropriate for this study's dataset as it works well with smaller samples. They also used the Toda–Yamamoto causality test to examine causal links. The ARDL cointegration results indicate a significant long-term relationship between CO_2 emissions, green technological innovation, nuclear energy consumption, and trade openness. Green technological innovation has a negative impact on CO_2 emissions. Higher nuclear energy consumption is associated with lower CO_2 emissions, while greater trade openness is associated with higher CO_2 emissions, although these effects are less certain. The results suggest promoting green technological innovation and nuclear energy can be effective strategies for reducing CO_2 emissions, while the impact of trade openness requires careful consideration due to its potential to increase emissions.

Keywords: nuclear energy consumption; green technological innovation; environment; trade openness; the United States

Citation: Jóźwik, B.; Topcu, B.A.; Doğan, M. The Impact of Nuclear Energy Consumption, Green Technological Innovation, and Trade Openness on the Sustainable Environment in the USA. *Energies* **2024**, *17*, 3810. https://doi.org/10.3390/en17153810

Academic Editors: Alina Cristina Nuta, Florian Nuta and Muhammad Hafeez

Received: 16 June 2024
Revised: 28 July 2024
Accepted: 1 August 2024
Published: 2 August 2024

1. Introduction

The global warming induced by the increase in CO_2 emissions at the global level poses serious challenges in terms of environmental sustainability. According to statistics from the Energy Information Administration (EIA), the increase in global carbon dioxide emissions has reached approximately 64% between 1990 and 2019, and it is projected to exceed 45% compared to the year 2000 by 2030. The primary cause of this increase is attributed to the heavy reliance of developing countries on fossil-based energy sources [1]. One of the most effective strategies in combating global climate change involves using cleaner energy sources that can replace fossil-based energy, particularly electricity generation. Renewable energy and nuclear energy are prominently featured among these cleaner energy sources. Nuclear energy is a significant non-carbonizing energy source capable of generating electricity within global energy production systems [2]. Global warming and climate change challenges urge nations to transition from fossil-based energy to electricity generation from cleaner energy sources. In this regard, nuclear energy holds significant importance for policymakers [3]. This is because nuclear energy not only contributes to a reduction in CO_2 emissions [4] but also facilitates economic growth by enabling electricity generation at lower costs [5,6].

However, the advantages and disadvantages of nuclear power economics must be addressed. For example, Böse [7] questions the nuclear scale-up in energy scenarios by investigating proposed technology scale-up thresholds for low-carbon scenarios. Sovacool [8] noted that nuclear power does not directly emit greenhouse gas emissions, but rather, it occurs through a "lifecycle": plant construction, operation, uranium mining and milling, and plant decommissioning. Macfarlane, Krall, and Ewing [9] also highlight the nuclear waste issues related to small modular reactors. In addition, although nuclear power accidents are decreasing in frequency, they are increasing in severity [10]. Sovacool [11] found a very interesting relationship in other research: a negative association between national nuclear and renewable energy attachment scales. This suggests that nuclear and renewable energy attachments tend to crowd each other out. In light of these factors, the future of nuclear power remains a complex and contentious issue, requiring careful consideration of its potential benefits and inherent risks. It also ought to be underlined that our research and assessments are focused solely on the impact of nuclear energy on carbon dioxide emissions.

The United States has a significant infrastructure for nuclear energy, with data from the EIA indicating that as of 1 August 2023, the country operates 54 commercial nuclear power plants. These plants house a total of 93 nuclear reactors distributed across 28 states. Efforts to increase capacity in these plants have ensured that the entire fleet of operational nuclear reactors maintains high capacity utilization rates [12]. This high efficiency has been a key factor in nuclear energy, contributing approximately 19–20% of the total annual electricity generation in the U.S. from 1990 to 2021 [13]. The existing nuclear fleet is the oldest globally, with an average age of 41.6 years [14].

Understanding the relationship between nuclear energy production capacity and actual generation is important for comprehending the role of nuclear power in the US energy mix. Figure 1 illustrates the US nuclear electricity production capacity and output from 2000 to 2022. This figure shows that nuclear energy production has consistently been within the capacity limits.

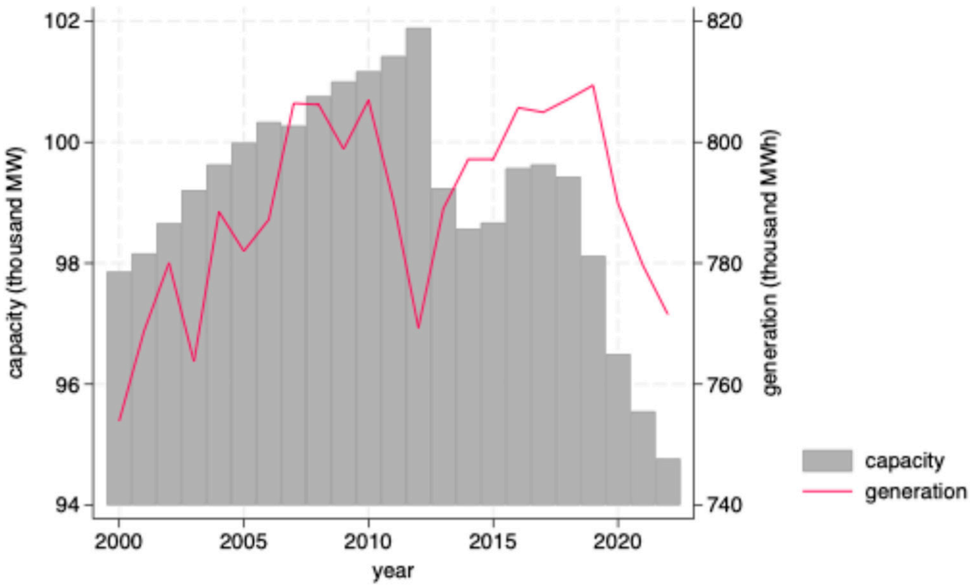

Figure 1. The US nuclear energy production capacity and generation (2000–2022). Source: EIA database.

The data presented in Figure 1 highlight the stability and efficiency of nuclear energy production in the US. Over the years, capacity has seen slight fluctuations, but overall generation has remained robust, with slight year-to-year variations. Notably, using nuclear energy is a potential driver for environmental quality. Guo et al. [15] assert in the literature that nuclear energy efficiency reduces CO_2 emissions, similar to Lin and Ullah [16]. Numerous studies in the literature also reach similar conclusions [2,17–22].

Based on the above results, this study aims to develop a sustainable solution for reducing CO_2 emissions by investigating the connection between nuclear energy and the environment for the significant potential of the US economy from 1990 to 2019. The potential contribution of this study is threefold: (i) Although previous literature has investigated the effect of nuclear energy on environmental sustainability, this study is the first to estimate this relationship in the context of green technology innovation (GTI) and trade openness using the example of the US, which ranks first in nuclear energy consumption. (ii) Secondly, this study focuses on nuclear energy usage and addresses the potential roles of GTI and trade openness in improving environmental quality. (iii) Furthermore, this study provides recommendations to policymakers for fulfilling the US' commitments in the Paris Agreement by identifying the impact of nuclear energy on carbon dioxide emissions. (iv) The study findings are important for regulating future GTI strategies and energy policies. A better understanding of the effects of nuclear energy consumption, GTI, and trade openness on environmental quality could assist in directing environmental protection and sustainable development efforts more effectively.

The other parts of the research are structured as follows: Section 2 presents relevant literature regarding the variables included in the environmental sustainability model. Section 3 outlines the employed model and methodology. Section 4 details predictions concerning the findings and discussion. This study ends with the conclusion and policy recommendations provided in Section 5.

2. Literature Review

2.1. Green Innovation and Environment

Technological advancements have significantly impacted various economic sectors worldwide in the past decade. Recently, researchers have increasingly focused on how green technological innovations influence ecological systems. In the literature, "green technological innovation" often refers to developing environmentally friendly products and processes that aim to balance economic needs with environmental and social demands [23]. Green innovation encompasses various aspects, such as minimizing energy and water consumption, optimizing raw materials, reducing waste and emissions, and utilizing bioinformatics, nanotechnology, and biotechnology [24].

Recent studies have indicated that green technology innovation can improve environmental quality significantly [25–28]. Furthermore, Hart and Dowell [29] argue that GTI can provide companies with a competitive edge while benefiting the environment. The latest research results suggest that GTI can also help increase production capacities and reduce environmental degradation [30–35]. Hence, GTI is being viewed as a key strategy to address global environmental issues and achieve sustainable development goals [36–40].

Contrary to the positive effects that have been noted, some studies find that GTI might increase carbon emissions due to the "rebound effect" and "green paradox". Fernández et al. [41], Dauda et al. [42], and Rennings and Rammer [43] argue that markets alone do not promote GTI effectively, emphasizing the need for incentives or regulations to encourage firms to adopt GTI. Additionally, Mongo et al. [44] add that as GTI progresses, production and energy consumption rise, potentially increasing emissions. Conversely, other studies indicate that GTI does not significantly impact environmental quality. These findings are often linked to countries' income and development levels [45–48]. The impact of GTI appears to vary over time and depends on factors such as pollution and income levels [49]. Research results demonstrate that the effect of GTI is stronger in high-income countries [50–52]. Furthermore, GTI effectively reduces emissions when they are high [53,54].

2.2. Nuclear Energy and Environment

Nuclear energy is considered a crucial player in minimizing the environmental impact of global energy consumption as a low-carbon energy source [2,19,21,55–58]. This potential for reducing environmental damage has caught the attention of policymakers globally.

Supporting this perspective, Cakar et al. [59] found that modern nuclear power plants enhance energy efficiency and environmental health by lowering greenhouse gas emissions through innovation. Many studies agree that nuclear energy is a temporary low-carbon energy source that helps cut carbon emissions from burning fossil fuels [14,60–64].

However, it is important to consider the contrasting views of some researchers. Sarkodie and Adams [65] and Mahmood et al. [66] argue that nuclear energy negatively impacts environmental quality. Similarly, Sadiq et al. [37] found that nuclear energy harms environmental sustainability. Adding to the complexity, Saidi and Mbarek [67] found nuclear energy to be ineffective at preserving environmental quality, and Kartal [68] found no significant impact of nuclear energy on carbon emissions. These studies and those mentioned earlier [7–9] suggest that issues like radioactive waste, operational inefficiencies, and global nuclear waste management restrictions could negatively impact the environment. Consequently, these conflicting research results point to the complex issue of nuclear energy's impact on the environment and public health. It also indicates the need to search for new technologies and energy sources.

2.3. Trade Openness and Environment

Studies on this subject have highlighted four main hypotheses: (1) the promotion hypothesis, (2) the inhibition hypothesis, (3) the feedback hypothesis, and (4) the neutral hypothesis. According to the promotion hypothesis, increasing trade openness promotes environmental quality. This hypothesis argues that trade openness facilitates the dissemination of environmental technologies and practices by stimulating economic growth and welfare [69]. Conversely, the inhibition hypothesis suggests that trade openness increases environmental degradation. An increase in trade openness may lead to increased production and resource depletion, thus escalating environmental pollution [70]. The feedback hypothesis proposes a mutual interaction between trade openness and environmental variables. In other words, as trade openness increases, it affects environmental variables, while the state of environmental variables also influences trade openness [71]. However, the neutral hypothesis posits that there is no relationship between trade openness and environmental variables or that the relationship is uncertain [72].

Empirical studies provide mixed results on these hypotheses. For example, Zamil et al. [73] demonstrated a positive relationship between trade openness and carbon emissions in Oman, supporting the inhibition hypothesis. Similarly, Musah et al. [74] found that trade openness increases ED for D8 countries, while Gozgor [75] and Jun et al. [76] reported similar results for OECD countries and China, respectively. These findings also align with the inhibition hypothesis. On the other hand, some studies support the promotion hypothesis. Chebbi et al. [77], Shahbaz et al. [78], Zhang et al. [79], and Mutascu and Sokic [80] found that trade openness could significantly reduce the growth of energy pollutants and thus enhance environmental quality. Similarly, Shahzad et al. [81], Mahmood et al. [3], and Sun et al. [82] determined that trade openness increases environmental quality, consistent with the promotion hypothesis. Additionally, some research aligns with the neutral hypothesis. Mutascu [83] found a nonsignificant relationship between trade openness and carbon dioxide emissions, suggesting no clear link between these variables. As mentioned, the literature presents mixed findings, with different studies supporting different hypotheses. Therefore, additional research is required to clarify the conflicting results regarding the relationship between CO_2 emissions and trade openness.

To summarize the literature review in three areas related to the model, theoretical and empirical studies highlight GTI as a critical strategy for improving environmental quality and achieving sustainability goals. However, some note potential negative effects like the "rebound effect". Nuclear energy is recognized for its low-carbon benefits and potential to reduce emissions, though concerns about radioactive waste and operational inefficiencies persist. Trade openness's impact on the environment is debated through four hypotheses—promotion, inhibition, feedback, and neutral—with mixed empirical support, indicating the need for further research to clarify these relationships.

3. Methods

This study examines the effects of green technological innovation, nuclear energy consumption, and trade openness on environmental quality within the context of the US economy, which is a global leader in nuclear energy consumption. The dataset includes 30 annual observations from 1990 to 2019, chosen specifically due to the availability of GTI data for this period. To explore these relationships, the study employs a logarithmic regression model formulated as follows:

$$lnCO_{2\ it} = \alpha + b_1 lnGTI_{it} + b_2 lnNEC_{it} + b_3 lnTO_{it} + \varepsilon_{it} \quad (1)$$

The estimation equation is guided by the models of Danish, Ulucak, and Erdogan [2]; Jahanger et al. [22]; Chang et al. [30]; and Gozgor [75]. These established models provide a robust foundation for analyzing the impact of innovation, energy consumption, and trade on environmental outcomes. As illustrated in Table 1, carbon emissions in tonnes per capita indicate environmental performance. The development of GTI is measured as a percentage of all technologies. Trade openness is expressed as a percentage of GDP, reflecting the extent of a country's engagement in international trade. Finally, nuclear energy consumption is quantified in exajoules, representing the input-equivalent energy consumption.

Table 1. Variables, symbols, and data sources.

Variables	Symbol	Source
CO_2 emissions	lnCO_2	OECD Data Bank
Development of environment-related technologies	lnGTI	OECD Green Growth Indicators
Nuclear energy consumption	lnNEC	BP Statistical Review
Trade openness	lnTO	WB-WDI

This study employs several unit root tests to ensure the stationarity of the data series, which is a prerequisite for reliable estimation results. Traditional unit root tests that are commonly used in empirical studies, such as ADF, PP, and KPSS, have low power, especially for small samples. These limitations reduce the reliability of these tests. In response to the low power problem of these tests, a new unit root test such as DF-GLS has been developed by Elliott et al. [84]. It provides more effective results than the ADF test due to its asymptotic distribution. Performing the DF-GLS test requires detrending the time series, which is calculated using the following regression equation:

$$\Delta x_t^d = \beta_1 x_{t-1}^d + \sum\nolimits_{i=1}^{k} \lambda_i \Delta x_{t-1}^d + \varepsilon_t \quad (2)$$

In Equation (2), x_t^d represents the detrended series. In this test, when the hypothesis H_0 defined as $\beta_1 = 0$ is rejected, the series x_t is stationary.

Additionally, we utilize the Lee and Strazicich LM unit root test [85] with a structural break. This test indicates the presence of a unit root in the series while accepting the alternative hypothesis H_1, which indicates that the series is stationary with structural breaks. The equation for the test with double structural breaks is as follows:

$$\Delta y_{t=\delta \Delta Z_t} + \phi \overline{S}_{t-1} + \mu_t \quad (3)$$

In the next step, the cointegration relationship among the variables is identified. To assess cointegration, Engle and Granger [86] tests, Johansen [87] tests, and Johansen and Juselius [88] tests are commonly utilized. The application of these tests depends on all series being stationary at the same level. This restriction does not apply in the ARDL bounds testing approach. This method detects a cointegration relationship as long as the series are not I(2) [89]. Furthermore, according to Narayan and Narayan [90] and Sahbaz et al. [91], the ARDL method provides more effective results for smaller samples than classical cointegration tests. The long-term logarithmic representation of the ARDL model is as follows:

$$\Delta InCO_{2_{it}} = \delta_{0i} + \delta_{1i} InCO_{2_{i,t-1}} + \delta_{2i} lnGTI_{i,t-1} + \delta_{3i} lnNEC_{i,t-1} + \delta_{4i} lnTO_{i,t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta InCO_{2_{i,t-j}} + \sum_{j=0}^{q1} \beta_{1ij} \Delta lnGTI_{i,t-j} + \sum_{j=1}^{q2} \beta_{2ij} \Delta lnNEC_{i,t-j} + \sum_{j=1}^{q3} \beta_{3ij} \Delta lnTO_{i,t-j} + \mu_i + \varepsilon_{it} \quad (4)$$

where i = 1, 2, . . ., N and t = 1, 2, . . ., T. In Equation (4), ε_{it} represents the white noise term, Δ the I(1), and the variables are defined as in the model to be estimated. δ_{ki} (k = 1, 2, 3, 4) represents the long-term relationship, while the summation symbol represents the short-term error correction term. In the ARDL bounds test by Pesaran et al. [89], if the F-statistic exceeds the upper critical value, the existence of cointegration is confirmed by accepting the hypothesis H_1. Following this, an ECM based on the ARDL test is formulated to forecast short-term developments:

$$\Delta InCO_{2_{it}} = \vartheta_1 ECT_{t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta InCO_{2_{i,t-j}} + \sum_{j=0}^{q1} \beta_{1ij} \Delta lnGTI_{i,t-j} + \sum_{j=1}^{q2} \beta_{2ij} \Delta lnNEC_{i,t-j} + \sum_{j=1}^{q3} \beta_{3ij} \Delta lnTO_{i,t-j} + \mu_i + \varepsilon_{it} \quad (5)$$

Finally, the direction of causality between variables is investigated. In this study, the Toda–Yamamoto causality test was applied. The traditional Granger test [92] allows for determining causality between variables when the series are stationary and contain a cointegration relationship. However, the Toda–Yamamoto test does not consider whether the series is stationary or contains a cointegration relationship. A VAR model must be established first to apply this test, and the lag length (ρ) must be determined. Then, the maximum integration degree, denoted as d_{max}, is added to the lag length. Knowing these two values facilitates accurate model estimation, prevents data loss, and allows for more successful results at the level. The test statistic in this model is examined using the Wald test, which follows a chi-square distribution. The model of the test is represented in Equations (6) and (7) [93]:

$$Y_t = \varphi + \sum_{i=1}^{\rho+dmax} \alpha_{1i} Y_{t-1} + \sum_{i=1}^{\rho+dmax} \alpha_{2i} X_{t-1} + \mu_{1t} \quad (6)$$

$$X_t = \varphi + \sum_{i=1}^{\rho+dmax} \beta_{1i} X_{t-1} + \sum_{i=1}^{\rho+dmax} \beta_{2i} Y_{t-1} + \mu_{1t} \quad (7)$$

These estimation methods collectively ensure a comprehensive and reliable analysis of the effects of green technological innovation, nuclear energy consumption, and trade openness on environmental quality in the US economy.

4. Findings and Discussion

At the beginning of our analysis, we present the summary statistics and correlation matrix. An overview of the central tendencies, variability, and distribution characteristics of the variables under study is provided in Table 2. For example, only the median of lnGTI (2.018) is slightly lower than the mean, indicating a slight left skew. Other medians are very close to the mean, suggesting a symmetric distribution. Standard deviations indicate low variability in variables except lnGTI, which shows moderate variability in green technology innovation. Table 2 also outlines the correlation coefficients between these variables, illustrating their relationships and potential multicollinearity. For instance, a strong negative correlation exists between $lnCO_2$ and lnGTI (−0.809), indicating that higher levels of green technology innovation are associated with lower CO_2 emissions. Similarly, a strong positive correlation exists between lnGTI and lnTO (0.796), suggesting that higher trade openness is associated with increased development of green technologies.

Table 2. Summary statistics and correlation matrix.

	$lnCO_2$	lnGTI	lnNEC	lnTO
Mean	2.882	2.132	2.031	3.214
Median	2.935	2.018	2.057	3.216
Maximum	3.010	2.547	2.115	3.428
Minimum	2.670	1.764	1.825	2.984
Std. Dev.	0.110	0.284	0.082	0.139
Skewness	−0.667	0.230	−1.029	−0.118
Kurtosis	1.906	1.440	2.834	1.891
Obs.	30	30	30	30
$\ln CO_2$	1.000			
lnGTI	−0.809	1.000		
lnNEC	−0.226	0.423	1.000	
lnTO	−0.637	0.796	0.680	1.000

Figure 2 illustrates the graphs of the logarithmic series. The Bai–Perron test [94,95] identifies breaks for the model between 1998 and 2010.

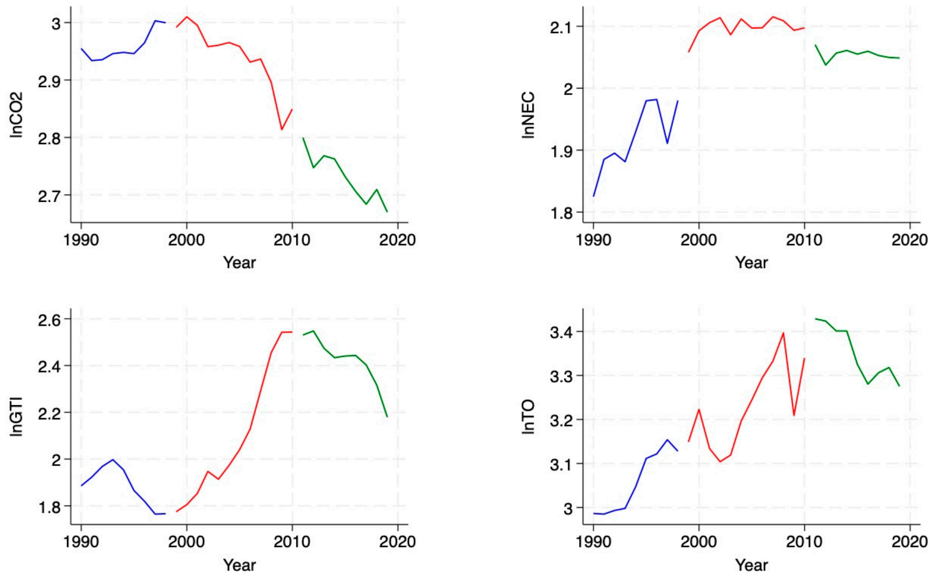

Figure 2. Graphs of logarithmic series with structural breaks for the model (Bai–Perron test). Note: structural breaks by Bai–Perron test: 1998 and 2010.

Table 3 presents the results of the DF-GLS unit root test, which determines whether a time series is stationary (i.e., it does not have a unit root) at levels (I(0)) or after differencing once (I(1)). $lnCO_2$ is non-stationary at level (I(0)), but becomes stationary after first differencing (I(1)) at a 1% significance level. lnGTI is stationary at both levels (I(0) and I(1)) at a 1% significance level, suggesting that lnGTI does not have a unit root. lnNEC and lnTO are non-stationary at level (I(0)), but become stationary after first differencing (I(1)) at a 10% significance level. These findings are critical for determining the appropriate econometric models for subsequent analysis, such as the ARDL bounds testing approach, which requires the variables to be integrated of order one, I(1), but not higher.

Table 4 presents the results of the Lee–Strazicich LM unit root test. This test determines whether a time series is stationary, accounting for structural breaks in the data. The table provides results for tests with both single and double structural breaks.

Table 3. DF-GLS test results.

Variables	I(0)	I(1)
	T-Statistic	**T-Statistic**
ln CO_2	0.569 (7)	−1.803 (7) ***
lnGTI	−1.747 (7) ***	−1.645 (7) ***
lnNEC	−1.302 (7)	−3.920 (7) *
lnTO	−1.222 (7)	−5.811 (7) *

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

Table 4. Lee Strazicich LM test results.

Variables	I(0)		I(1)	
	T	**Break**	**T**	**Break**
Results of the Test with Single Structural Break				
ln CO_2	−2.208 (3)	2015	−6.862 (1) *	2000
lnGTI	−4.446 (7) *	2001	−3.337 (4) ***	2005
lnNEC	−1.419 (6)	2006	−8.332(6) *	2011
lnTO	−3.284 (3) ***	2011	−6.759 (0) *	2000
Results of the Test with Two Structural Breaks				
ln CO_2	−7.488 (7) *	2006–2009	−9.521 (8) *	2005–2008
lnGTI	−6.357 (4) **	2005–2016	−5.854 (5) ***	1999–2014
lnNEC	−8.049 (7) *	2006–2009	−15.412 (6) *	2004–2011
lnTO	−5.872 (6)	2000–2008	−7.860 (8) *	2001–2011

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

The Lee–Strazicich LM unit root test results indicate that most series become stationary after accounting for structural breaks, either single or double. lnCO_2 and lnNEC show strong evidence of structural breaks impacting their stationarity at both levels. First differencing lnGTI demonstrates stability at both levels with structural breaks accounted for. lnTO becomes stationary after first differencing, with significant structural breaks impacting its stability. The Lee–Strazicich LM test provides additional insights by accounting for structural breaks, which the DF-GLS test does not consider.

Both tests generally agree on the stationarity of the variables after first differencing. The Lee–Strazicich LM test reveals the presence and impact of structural breaks, offering a more detailed and accurate assessment of stationarity for all variables. Understanding structural breaks is crucial for accurately modelling and forecasting these economic and environmental variables. These findings allow for using the preferred boundary test approach proposed by Pesaran [88] when variables are stationary at different levels. Furthermore, since none of the series are stationary at the I(2) level, the ARDL boundary test can be employed to observe the presence of long-term relationships.

Table 5 presents the results for determining the appropriate lag length for the Vector Autoregression (VAR) model. The selection criteria used include the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan–Quinn Information Criterion (HQ). Each criterion suggests the most appropriate lag length based on different aspects of model performance.

The highest-value LR (28.88605) at lag length 3 suggests this is the optimal lag length for capturing the dynamics in the data. The lowest-value FPE (4.62×10^{-12}) at lag length 3 indicates this lag length provides the best out-of-sample forecasting accuracy. The lowest-value AIC (−15.09714) at lag length 3, suggests it minimizes the information loss. The lowest-value SIC (−13.43529) at lag length 1 suggests it balances model fit and complexity. Still, considering SIC tends to penalize model complexity more heavily, it might suggest a shorter lag length. The lowest-value HQ (−14.35504) at lag length 3 indicates it is the preferred lag length considering model fit and complexity.

Table 5. Appropriate lag length of the Vector Autoregression model.

Lag Length	LR	FPE	AIC	SIC	HQ
0	NA	6.42×10^{-9}	−7.512015	−7.320039	−7.454931
1	177.5034	6.70×10^{-12}	−14.39517	−13.43529 *	−14.10974
2	18.16290	8.73×10^{-12}	−14.21903	−12.49125	−13.70527
3	28.88605 *	4.62×10^{-12} *	−15.09714 *	−12.60145	−14.35504 *

Note: * indicates 10% significance level.

In summary, most criteria suggest that a lag length of 3 is the most appropriate for the VAR model, as it provides the best model performance in terms of capturing the dynamics, minimizing forecasting errors, and balancing model fit and complexity. However, SIC suggests a lag length of 1, possibly due to its higher penalty for model complexity. Given the overall results, a maximum lag length of 3 is recommended and selected for the ARDL and the Toda–Yamamoto causality analysis.

The results of the ARDL cointegration analysis are presented in Table 6. The F-statistic of 16.163 is greater than the upper critical value (4.66) and provides strong evidence (at the 1% significance level) that the variables are cointegrated, confirming the existence of a long-term relationship. The optimal lag length of (3, 1, 1, 0) was determined, indicating that $lnCO_2$ requires three lagged terms to best capture its dynamics, while lnGTI and lnNEC each require one lagged term, and lnTO does not require any lagged terms. The significant and negative error correction term (ECTt-1) demonstrates that any short-term deviations from the long-term equilibrium are corrected at a moderate speed at 15.1% per period, ensuring the system returns to equilibrium over time, approximately after 6.66 years (1/0.15).

Table 6. ARDL cointegration results.

F-Bounds Test	Model
	F($lnCO_2$/lnGTI, lnNEC, lnTO)
Optimal Lag Length	(3, 1, 1, 0)
ECT_{t-1}	−0.151 ***
F-statistics	16.163 ***

Note: *** indicates a 1% significance level.

Table 7 presents the long-term estimation results for the ARDL model, along with several diagnostic tests to assess the model's robustness and validity. The constant term is significant at the 1% level, indicating a strong baseline level of CO_2 emissions when all independent variables are zero. lnGTI has a significant negative impact on $lnCO_2$ at the 5% level, suggesting that an increase in green technology innovation leads to a reduction in CO_2 emissions. lnNEC and lnTO have a less significant impact on $lnCO_2$ at the 10% level, indicating that higher nuclear energy consumption is associated with lower CO_2 emissions and higher trade openness is associated with greater CO_2 emissions, although these effects are less certain. R-squared (0.988) indicates that 98.8% of the variance in $lnCO_2$ is explained by the independent variables. In terms of the adjusted R-squared (0.983), adjusted for the number of predictors, 98.3% of the variance in $lnCO_2$ is explained, suggesting a very good model fit. F-statistics (194.238) with a p-value of 0.000 suggest that the overall model is highly significant at the 1% level, indicating that the independent variables collectively impact the dependent variable. The model passes all diagnostic tests, suggesting no issues with serial correlation, heteroscedasticity, the normality of residuals, or model misspecification.

Table 7. ARDL long-term estimation and diagnostic test results.

Variables	Coefficient	t	*p*
Constant	5.491 ***	4.745	0.000
lnGTI	−1.243 **	−2.600	0.018
lnNEC	−1.996 *	−1.990	0.061
lnTO	1.233 *	1.794	0.089
R^2	0.988		
Adjusted R^2	0.983		
F-statistics	194.238		0.000
Diagnostic Test Results			
B-Godfrey LM Test	1.293		0.271
ARCH LM Test	1.284		0.306
Ramsey Reset Test	0.283		0.601
J-B Normality Test	1.271		0.529

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

Additionally, autocorrelation and heteroscedasticity in the model were examined using the Breusch–Godfrey LM test and ARCH LM test, respectively (Table 7). The *p*-values greater than the 0.05 significance level confirm the absence of these problems. A Ramsey RESET test was conducted to investigate whether there was a specification error in the model, and it was determined that there was no error. Furthermore, by applying the Jarque–Bera normality test to the residuals of the model, it was concluded that these values followed a normal distribution.

Figure 3 illustrates the results of the CUSUM and CUSUMSQ tests developed by Brown et al. [96] to measure the stability of long-run coefficients. Both tests indicate that the ARDL model's coefficients are stable over the sample period from 2002 to 2018. The lines in both tests remain within the 5% significance boundaries, suggesting no significant structural breaks in the model. This stability is crucial for the reliability of the model's long-term estimates and confirms the robustness of the results presented in the study.

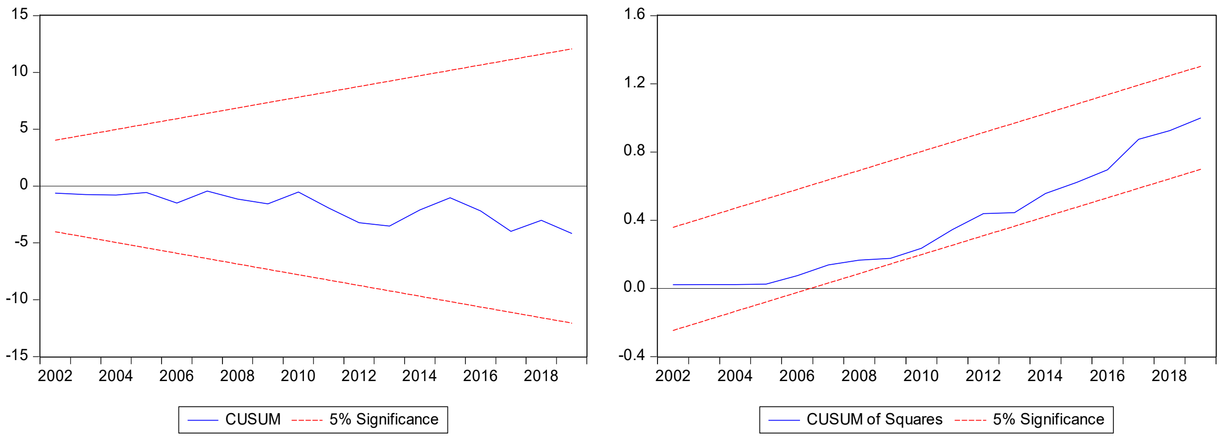

Figure 3. CUSUM and CUSUMSQ test results.

The findings obtained in the study regarding the impact of nuclear energy consumption on environmental quality are consistent with several prior studies. The results align with those of Anwar et al. [17], Jahanger et al. [22], Lee et al. [60], Pao and Chen [61], Saidi and Omri [62], Nathaniel et al. [63], Majeed et al. [64], and Rehman et al. [97], which also observed a positive impact of NEC on environmental quality. These studies collectively suggest that increased use of nuclear energy contributes to better environmental outcomes. However, the study's findings contrast with those of Sadiq et al. [18], Sarkodie and Adams [65], Mahmood et al. [66], Saidi and Mbarek [67], Al-Mulali [98], and Jin and Kim [99], which found that nuclear energy leads to environmental degradation. This discrepancy highlights the ongoing debate and complexity surrounding the environmental impacts of nuclear energy.

Similarly, the positive effect of green technology innovation on environmental sustainability observed in this study supports the conclusions of Chang et al. [30], Ganda [31], Tang et al. [32], Wang et al. [33], and Mighri and Sarkodie [35]. These studies emphasize the role of technological advancements in promoting environmental sustainability by reducing emissions and improving energy efficiency. Conversely, this finding contradicts the results of Fernández et al. [41], Dauda et al. [43], and Mongo et al. [44], who found that GTI can lead to environmental degradation. These conflicting results indicate that the relationship between technological innovation and environmental outcomes may be context-dependent, influenced by factors such as implementation practices and regional policies.

Moreover, the study found a positive impact of trade openness on CO_2 emissions. Specifically, a 1% increase in lnTO leads to a 1.233% increase in $\ln CO_2$, indicating that trade openness has a detrimental effect on environmental quality in the US. This finding is consistent with the inhibition hypothesis, supported by studies such as Zamil et al. [73], Musah et al. [74], Gozgor [75], Jun et al. [76], and Su and Moaniba [100]. These studies suggest that increased trade can exacerbate environmental degradation by fostering industrial activities that lead to higher emissions. However, the study's findings are at odds with those supporting the promotion hypothesis, such as Chebbi et al. [77], Shahbaz et al. [78], Zhang et al. [79], Mutascu and Sokic [80], Hussain et al. [101], Khurshid et al. [102], and Ma et al. [103]. These studies argue that trade openness can enhance environmental quality by facilitating the transfer of green technologies and promoting stricter environmental standards through international cooperation.

In the final step, the causality is examined. The Toda–Yamamoto causality test results in Table 8 reveal that green technology innovation has a significant unidirectional causal effect on CO_2 emissions. A significant bidirectional causality exists between nuclear energy consumption and CO_2 emissions, indicating mutual influence. There is also significant bidirectional causality between trade openness and CO_2 emissions, suggesting reciprocal effects.

Table 8. Toda–Yamamoto test results.

Causality Direction	Chi^2	p	Decision
$\ln GTI \rightarrow \ln CO_2$	59.489	0.000	$GTI \Rightarrow CO_2$
$\ln CO_2 \rightarrow \ln GTI$	6.786	0.147	
$\ln NEC \rightarrow \ln CO_2$	19.397	0.000	$NEC \Leftrightarrow CO_2$
$\ln CO_2 \rightarrow \ln NEC$	8.638	0.070	
$\ln TO \rightarrow \ln CO_2$	10.631	0.031	$TO \Leftrightarrow CO_2$
$\ln CO_2 \rightarrow \ln TO$	17.964	0.001	

Note: $\Rightarrow$ and $\Leftrightarrow$ indicate unidirectional and bidirectional causality, respectively.

The finding of bidirectional causality between nuclear energy and CO_2 emissions in this study is consistent with the findings of Majeed et al. [64] and Murshed et al. [21]. However, this result differs from the unidirectional causality detected from NE to CO_2 emissions by Pata and Samour [20] and Jóźwik et al. [58]. Regarding the unidirectional causality running from green technology innovation to carbon dioxide emissions identified in the study, it aligns with the findings of Lingyan et al. [54] and Razzaq et al. [104], but it is not consistent with the study by Qin et al. (2021) [105], which detected bidirectional causality between these two variables. Lastly, the finding of bidirectional causality between trade openness and CO_2 emissions is similar to the study by Musah et al. [74] but contradicts the unidirectional causality running from TO to carbon dioxide emissions found by Jun et al. [76].

5. Conclusions and Policy Recommendations

One of the primary causes of global warming is the emission of large quantities of greenhouse gases into nature during human activities and production processes, with CO_2 emissions being a major contributor. To address the issue of global warming worldwide, there is an increasing necessity to reduce the use of fossil-based energy resources and shift towards alternative energy sources, such as nuclear energy.

This study found that nuclear energy (although this effect is less certain) and green technology innovation improve environmental quality in the US. At the same time, trade openness leads to increased carbon dioxide emissions. Additionally, according to the results of the Toda–Yamamoto causality test, a unidirectional causality relationship from green technology innovation to CO_2 emissions and a bidirectional causality relationship between nuclear energy and carbon dioxide emissions have been identified. These results align with previous findings that highlight the positive impact of green technology innovation on environmental quality, supporting the notion that technological advancements are crucial for promoting sustainability [25–27]. Additionally, identifying bidirectional causality between nuclear energy and CO_2 emissions reinforces the findings of Majeed et al. [64] and Murshed et al. [21], providing further evidence of the interdependent relationship between nuclear energy use and environmental outcomes. This paper also contributes to the ongoing debate about the impact of trade openness on environmental quality by confirming a bidirectional relationship consistent with Musah et al. [74].

The outcomes of the analysis can provide policymakers with significant information. The increase in the use of nuclear energy can reduce carbon dioxide emissions, contributing to environmental sustainability, while ensuring safe practices as discussed in the literature review. The US government can establish incentive programs and provide financial support to promote nuclear energy. These incentives can be used for the modernization of existing facilities and the construction of new nuclear power plants. Furthermore, incentives should be provided for innovation, research, and development activities in nuclear energy technologies. However, considering the research results indicating the threat of nuclear energy, strict inspections and regulations should be in place to ensure nuclear power plants' safety and environmental compliance. For example, enhancing safety standards and monitoring waste management processes can help mitigate environmental risks. Additionally, considering the environmental impacts of international trade seems crucial. Especially harmonizing environmental standards at the international level and promoting green trade agreements can ensure that trade is in line with environmental sustainability.

However, this study has several limitations. Firstly, the dataset covers the period from 1990 to 2019, which might not capture the most recent changes and policies in nuclear energy and green technological innovation. Secondly, the analysis focuses solely on the USA, limiting the generalizability of the findings to other countries. Thirdly, measuring the impact of green technological innovation can be challenging, as the metrics and indicators used may not fully capture all dimensions of innovation. Fourthly, our model does not take into account other factors, particularly other energy generation technologies, that could influence environmental quality. Lastly, trade openness is measured only by trade volume without considering the quality of trade.

Future research could address these limitations by conducting similar analyses for different countries and regions, providing comparative insights into the effects of nuclear energy and green technological innovation on environmental quality. Additionally, a detailed analysis of the components of green technological innovation, such as energy efficiency technologies and renewable energy technologies, could identify which innovations have the most substantial impact on environmental quality. Finally, considering the quality and nature of trade in addition to trade volume could provide a more nuanced understanding of how trade openness affects environmental outcomes, especially when promoting the trade of environmentally friendly products. These directions would enhance the comprehensiveness and depth of future research on this critical topic.

Author Contributions: All authors contributed equally to the paper. All authors have read and agreed to the published version of the manuscript.

Funding: The APC was funded by the John Paul II Catholic University of Lublin.

Data Availability Statement: The data (variables) can be found at: EIA, U.S. nuclear industry, https://www.eia.gov/energyexplained/nuclear/us-nuclear-industry.php, Date of Access: 5 March 2024; Natural Resources Defense Council (NRDC), Paris Climate Agreement: Everything You Need to Know, Date of Access: 5 March 2024, https://www.nrdc.org/stories/paris-climate-agreement-everything-you-need-know#sec-whatis; United Nations Climate Change (UNCC), What is the Paris Agreement?, Date of Access: 6 March 2024, https://unfccc.int/process-and-meetings/the-paris-agreement; Statista. Leading Countries in Nuclear Energy Consumption Worldwide in 2022. Available online: https://www.statista.com/statistics/265539/nuclear-energy-consumption-in-leading-countries/ (accessed on 5 March 2024).

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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