IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(5), 96-102.

EJ EconJournals

Energy Price Uncertainty and Renewable Energy Consumption: A Nonlinear Analysis

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Received: 10 March 2025 **Accepted:** 28 June 2025 **DOI:** https://doi.org/10.32479/ijeep.19639

ABSTRACT

In this study, we conduct an in-depth examination of the intricate relationship between energy uncertainty and renewable energy consumption. Understanding this dynamic is crucial, as energy uncertainty-characterized by volatility in energy prices, policy shifts, and supply chain disruptions-can significantly influence the adoption and utilization of renewable energy sources. To explore this relationship, we employ a nonlinear Granger causality test based on artificial neural networks. This advanced methodology allows us to capture complex and nonlinear dependencies that traditional econometric models may overlook. Our empirical findings reveal that fluctuations in the energy uncertainty index play a pivotal role in forecasting changes in renewable energy usage within the industrial sector. Specifically, periods of heightened uncertainty correspond with noticeable shifts in renewable energy consumption, suggesting that businesses may adjust their energy strategies in response to uncertainty-driven risks. These insights hold significant implications for industry stakeholders, policymakers, and energy investors. A clearer understanding of the influence of energy uncertainty on renewable energy adoption can aid in formulating more resilient energy management strategies. Furthermore, policymakers can design regulatory frameworks that mitigate the adverse effects of uncertainty, fostering a more stable and predictable environment for industrial renewable energy investment.

Keywords: Energy Uncertainty, Renewable Energy Consumption, Artificial Neural Networks, Granger Causality Test
JEL Classifications: Q42; Q48; C45

1. INTRODUCTION

In recent years, the shift towards renewable energy has gained significant attention, driven by concerns about climate change, energy security, and the need for sustainable development (Noailly and Smeets, 2015; Haldar and Sethi, 2022; Feng and Zheng, 2022). The use of renewable energy resources, including solar, wind, hydropower, and bioenergy, has emerged as a crucial strategy for reducing dependence on fossil fuels and mitigating environmental degradation (Gozgor, 2018; Lu et al., 2021). As global economies transition towards greener energy solutions, understanding the factors that influence renewable energy consumption becomes crucial. One such factor is economic policy uncertainty (EPU), which has drawn increasing attention in the literature due to its potential impact on energy markets and investment behaviors.

A growing body of literature has examined the effects of economic policy uncertainty (EPU) on renewable energy consumption (Sendstad and Chronopoulos, 2020; Feng and Zheng 2022; Chu and Le, 2022; Ogede et al., 2023). Research consistently highlights EPU as a key factor influencing renewable energy uptake (Zeng and Yue, 2022; Lu et al., 2021; Romano and Fumagalli, 2018, among others). High levels of EPU often result in delays or cancellations of renewable energy projects (Shafiullah et al., 2021), thereby reducing overall consumption. Additionally, EPU can dampen future income expectations, discouraging firms from taking on higher risks, which further limits investment in renewable energy (Borozan, 2022). Ivanovski and Marinucci (2021) confirm a long-term negative relationship between EPU and renewable energy consumption, while Zeng and Yue (2022) show that this trend is particularly pronounced in BRICS countries. Similarly, Sohail et al. (2021) found that monetary policy uncertainty negatively affects renewable energy consumption in both the short and long term. Economic policy uncertainty refers to the lack of clarity or predictability regarding a government's future economic policies. It can arise from political instability, changes in fiscal or monetary policy, regulatory reforms, or trade disputes. High levels of uncertainty can lead to delayed investments, reduced consumer spending, and changes in business strategies, all of which could impact energy consumption patterns (Vitenu-Sackey and Acheampong, 2022). Given the capital-intensive nature of renewable energy projects, uncertainties in policy frameworks or government incentives could significantly affect decisions related to investment and adoption of renewable energy technologies (Dhakouani et al., 2019; Lu et al., 2020).

The relationship between economic policy uncertainty and energy consumption, particularly renewable energy, has garnered increasing attention due to its implications for global energy transitions. Owusu et al., (2024) highlight how uncertainty can influence energy demand, as firms and consumers may postpone energy-related investments during periods of heightened economic unpredictability. Similarly, Ivanovski and Marinucci (2021) found that higher levels of EPU negatively impact renewable energy consumption, potentially dampening efforts to meet energy security and environmental goals. Their study highlights the importance of accounting for country-specific economic risks when designing policies to foster renewable energy adoption. This finding is further supported by Feng and Zheng (2022), who noted that, while EPU generally promotes renewable energy innovation, this effect varies across countries. Specifically, countries with high institutional quality, particularly within the OECD, experience more significant growth in renewable energy innovation under EPU. Furthermore, Lu et al. (2021) explored the influence of EPU on renewable energy consumption in sub-Saharan Africa, revealing that EPU has a long-term negative effect on renewable energy uptake in the region. Their findings suggest that foreign direct investment (FDI) and financial growth are critical mediators in the relationship between EPU and renewable energy use, highlighting the complexity of energy policy in economically vulnerable regions. Similarly, Borojo et al. (2023) examined the role of governance and technological innovation in mitigating the adverse effects of EPU on green growth in emerging economies. Their study demonstrates that strong governance and sustainable innovation can offset the negative impact of EPU on environmental performance. Zhang et al. (2021) investigated the EPU-renewable energy nexus in BRIC nations, focusing on the role of FDI and financial development. They found that while EPU negatively affects renewable energy consumption, increased FDI and financial sector development help alleviate this impact, suggesting that robust financial mechanisms are essential for promoting clean energy transitions in uncertain policy environments. Furthermore, Aytac (2023) explored the relationship between global EPU and energy prices, showing an asymmetric effect of EPU on fossil fuel prices, particularly during periods of global economic expansion, which further complicates energy market dynamics. Wei et al. (2021) examined the dynamic co-movement and cointegration relationships between economic policy uncertainty (EPU) and various energy productions in China, including coal, natural gas, crude oil, electricity, and renewable energy, from January 1995 to October 2019. The study finds that while short-term co-movement is strong between energy production and EPU, the relationship weakens over the long term, suggesting a positive causality, with further policy recommendations based on these findings. Guliyev (2023) explores the impact of renewable energy consumption on economic growth in G7 countries, focusing on the potential nonlinear relationship between these variables. The analysis reveals an asymmetric long-run cointegration relationship in Canada and the U.S., while the overall panel data analysis indicates a positive but statistically insignificant long-term relationship between renewable energy consumption and economic growth across all G7 countries.

In this study, we investigate non-linear and complex dynamics between energy policy uncertainty and renewable energy consumption. Recent advancements in econometric techniques, particularly the application of non-linear models, offer new perspectives on understanding these complex relationships. Non-linear methods allow for the capture of intricate interactions that might be missed in traditional linear frameworks. For instance, artificial neural networks (ANNs) have become a popular tool in forecasting and modeling time series data due to their ability to handle non-linearities and capture hidden patterns in data (Hmamouche, 2020). In this context, the present study seeks to explore the relationship between economic policy uncertainty and renewable energy consumption by employing a non-linear Granger causality test based on ANNs.

The use of artificial neural networks (ANNs) in economic and energy studies has gained traction due to their ability to capture nonlinear dependencies and intricate causality structures. Unlike conventional time-series models, which assume fixed relationships over time, ANNs can adaptively learn patterns in data, making them well-suited for analyzing the dynamic nature of energy price uncertainty and its impact on renewable energy consumption. By integrating a nonlinear Granger causality test with ANNs, this study provides a more nuanced understanding of how uncertainty in energy markets influences renewable energy adoption decisions. The rationale for focusing on non-linear Granger causality stems from the need to capture the complex and potentially asymmetric effects of energy policy uncertainty on renewable energy consumption. Traditional Granger causality tests, based on linear models, might not fully account for the non-linear interactions between the variables, particularly in the context of rapidly evolving energy markets and policy landscapes. By utilizing ANNs, we aim to enhance the robustness and accuracy of our causality analysis, providing a more comprehensive understanding of how energy policy uncertainty influences renewable energy consumption over time.

Recent studies have extensively examined the role of energy price fluctuations in influencing economic and environmental policies. However, limited attention has been given to the nonlinear effects of energy price uncertainty on renewable energy consumption, particularly within the industrial sector. Traditional econometric models often assume linear relationships, which may overlook complex interactions and threshold effects. This study aims to fill this gap by employing a nonlinear Granger causality framework based on artificial neural networks, offering a novel approach to understanding this intricate relationship. In other words, this study contributes to the existing literature in several ways. First, it extends the analysis of the relationship between energy policy uncertainty and renewable energy consumption by incorporating a non-linear framework, addressing the limitations of previous linear models. Second, it applies an ANN-based Granger causality approach, which offers a more flexible and accurate means of detecting causality in complex time series data. Finally, this research provides valuable insights for policymakers and stakeholders in the energy sector, highlighting the importance of stable and predictable energy policies in promoting renewable energy adoption. Specifically, we apply a non-linear Granger causality test using artificial neural networks (ANNs) to examine how energy policy uncertainty predicts changes in renewable energy consumption. The choice of ANN-based Granger causality allows us to model the non-linear interactions between the variables, overcoming the limitations of traditional linear causality tests (Baek and Brock, 1992). In particular, we use a feedforward ANN structure within a Vector Autoregressive Neural Network (VARNN) framework, which incorporates lagged values of both economic policy uncertainty and renewable energy consumption to predict future changes in renewable energy use.

Understanding the nonlinear effects of energy price uncertainty is crucial for policymakers and industry stakeholders aiming to promote renewable energy integration. If uncertainty has a significant impact on investment decisions, policy interventions may be required to stabilize energy markets and encourage sustainable energy transitions. By offering empirical evidence on this relationship, our study provides valuable insights for designing market-based mechanisms and regulatory frameworks that mitigate uncertainty-related risks and foster renewable energy adoption in industrial settings.

The remainder of the paper is structured as follows: Section 2 outlines the methodology employed in our analysis. Section 3 provides an overview of the data, while Section 4 presents the findings on the non-linear causal relationship between Bitcoin price volatility and Bitcoin-related energy consumption. Finally, Section 5 offers concluding remarks.

2. METHODS

2.1. Nonlinear Granger Causality Test

Granger causality is widely recognized as a robust method for identifying causal relationships between variables. When applied across different frequency bands, this method is particularly effective in capturing the varying strength and direction of causality, which can differ across frequencies. Granger (1969; 1980) introduced the spectral-density approach, offering a more nuanced and detailed depiction of causality than a single, uniform application of Granger causality across all periodicities. As a result, measuring bivariate Granger causality across the frequency spectrum is more informative and efficient than traditional single-frequency tests. In this context, two main issues emerge: First, how causality changes with frequency, and second, whether the results and directionality observed in standard time-domain Granger causality tests hold when examined across different frequency bands.

However, linear causality tests, including the Granger causality test, may lack the power to detect non-linear causal relationships, as pointed out by Baek and Brock (1992) and Hiemstra and Jones (1994). In other words, these tests may fail to capture non-linear patterns that could be predictive of future values. Two significant concerns arise regarding the statistical properties of these tests when applied to residuals from Vector Autoregressive (VAR) models. Baek and Brock (1992) argue that their modified test retains the same asymptotic distribution, whether the residuals are independent and identically distributed (iid) or consistently estimated from a VAR model. This characteristic, known as nuisance-parameter-free (NPF), simplifies the testing procedure. We anticipate that the modified test employed in this study will similarly exhibit NPF properties. Despite this advantage, Hiemstra and Jones (1993) provide Monte Carlo evidence showing the robustness of the modified test to nuisance parameters. They also demonstrate a strong correspondence between the asymptotic and finite-sample properties of the test when applied to VAR model residuals.

To address the limitations of linear causality tests, this paper introduces a non-linear test based on Artificial Neural Networks (ANNs), building on the work of Hmamouche (2020). This approach allows for the detection of non-linear relationships between time series data. Specifically, we propose a non-linear extension of the Granger causality test that utilizes feed-forward neural networks.

ANNs are particularly useful for capturing causal relationships in time series that exhibit non-linear dynamics. In this paper, we harness the capabilities of ANNs by employing a Vector Autoregressive Neural Network (VARNN) model within an extended Granger causality framework. The following section provides a brief overview of the VARNN model and its role in this approach.

2.2.1. Granger causality selection on encoding

This study employs a Vector Autoregressive Neural Network (VARNN) model to predict future values of a target variable (X). The model is designed for a *p*-dimensional stationary time series observed over T time points, using a training dataset that includes x and k predictor variables $\{x_1,\ldots,x_k\}$. The VARNN is built on a multi-layer perceptron (MLP), a type of feedforward artificial neural network (ANN), which incorporates lagged values of both the target variable and its predictors to forecast future values of x.

One of the key advantages of the VARNN is its flexibility in tailoring the prediction for each target variable with a unique set of predictors. This means that different target variables can be associated with different sets of predictors, making the model highly adaptable. For this study, the VARNN uses two hidden layers: the first with two neurons for univariate predictions, and the second with four neurons for bivariate predictions, as detailed in Equations 5 and 6.

To prepare the data for supervised learning, the VARNN reformats it based on the selected lag parameter. The model is trained using the stochastic gradient descent (SGD) algorithm, with a learning rate of 0.1 to update the network's weights. Following the approach outlined by Hmamouche (2020), the rectified linear unit (ReLU) activation function is used in the hidden layers, while the sigmoid function is applied in the output layer. This configuration helps the model efficiently learn and predict non-linear patterns in the data.

For the purposes of our empirical analysis, we consider the SGD algorithm. Subsequently, we define the global function of the VARNN (p) as follows:

$$x_t = \psi_{nn}(x_{t-1},\dots,x_{t-p},\dots,x_{k(t-1)},\dots,x_{k(t-k)}) + u_t \tag{1}$$

Where ψ_{nn} and u_t stand for the network function and the error terms, respectively.

In a manner similar to Granger causality analysis, we examine the relationship between two variables, x_t and y_t. To evaluate whether of x_t exerts a causal effect on y_t, we use two predictive models. The first model forecasts the target variable using only its own past values, while the second model includes both the lagged values of the target variable and the lagged values of the predictor variable to make predictions.

$$y_t = \psi_{1,nn}(y_{t-1},\dots,y_{t-p},\dots,y_{k(t-1)},\dots,y_{k(t-k)}) + u_{1,t} \tag{2}$$

$$y_t = \psi_{2,nn}(y_{t-1},\dots,y_{t-p},\dots,y_{t-1},\dots,y_{t-p}) + u_{2,t} \tag{3}$$

Where $\psi_{1,nn}$ and $\psi_{2,\mathrm{nn}}$ represent the network functions of the two models, respectively.

Causality testing utilizes F-statistics to evaluate whether the lagged values of a predictor variable x_t contribute statistically significant information about the target variable y_t, even when the past values of y_t are already included. In essence, the F-test assesses whether x_t has a causal influence on y_t that extends beyond the effects of y_t's own previous values. The null hypothesis being tested states that the lagged values of x_t do not Granger-cause the series y_t.

3. DATA

Data concern the Energy Uncertainty Index (EUI) covering a sample period from January 2001, to September 2022, with a monthly sampling frequency[1]. For the purposes of our analysis, we further use monthly data for the Renewable Energy Consumption sourced from the U.S. Energy Information Administration[2]. Specifically, the Renewable Energy Consumption Index refers to the total renewable energy consumed by the industrial sector, measured in trillion Btu. We have used the logarithmic differencing for the purposes of our analysis.

Table 1 reports the basic statistics of each variable. All series under consideration are on a yearly basis; we have considered the yearly average of the Energy Uncertainty Index data to proxy energy uncertainty. The logarithmic transformation of both variables has been considered throughout the analysis (Figure 1). As we can see from this table, the descriptive statistics for the logarithm of Renewable Energy Consumption variable, show a relatively symmetrical distribution with some noteworthy characteristics. The median of 5.261 is close to the mean of 5.191, suggesting a slight symmetry in the distribution. However, the skewness of −0.5035 indicates a leftward skew. The kurtosis of 1.8862 is <3, indicating a flatter distribution with lighter tails compared to a normal distribution. The Jarque-Bera test (Chi-squared value of 24.516 and a P-value=0.000), provides strong evidence against normality. Overall, these results suggest that while the renewable energy consumption data is relatively stable and less variable, there are still deviations from normality that should be considered in further analyses (Figure 2). The descriptive statistics for the logarithmic transformation of the energy uncertainty index (EUI) The descriptive statistics for the logarithm of the Energy Uncertainty Index reveal a left-skewed distribution with a significant concentration of higher values and heavy tails, as indicated by the skewness and kurtosis measures. The high standard deviation suggests considerable variability, while the Jarque-Bera test (p-value) leads to the rejection of the null hypothesis of normality[3].

Table 1: Descriptive statistics for each variable

Descriptive Statistics Measures	Energy uncertainty index	Renewable energy consumption industrial sector
	EUI_t	$RECIS_t$
Mean	3.0151	5.191
Median	3.0555	5.261
Maximum	4.4191	5.457
Minimum	−0.8769	4.833
Std. Dev.	0.6807	0.1474
Skewness	−1.5346	-0.5035
Kurtosis	8.4809	1.8862
J-B	429.14***	24.516***
J-B Prob.	[0.0000]	[0.0000]
Obs	261	261

This table reports descriptive statistics for the Energy Uncertainty Index (EUI) (in logarithmic transformation) and the logarithm of the Renewable Energy Consumption Index for the industrial sector monthly series. The following statistics are presented: Mean, median, maximum, minimum, standard deviation (Std. Dev), skewness, kurtosis, and Jarque Berra normality test (J-B). The Jarque-Bera test is used to assess whether the series considered are normally distributed. The *P* values from the test are presented in brackets below. Asterisks (***), indicate that we reject the null hypothesis of normality at a 1% significance level

4. RESULTS

We now proceed with the discussion of the empirical results by employing the VARNN(p) model to identify the non-linear causal relationship between the Renewable Energy Consumption Index for the industrial sector in the United States and Energy Uncertainty. Specifically, the results presented in Table 2 indicate a significant nonlinear Granger causality relationship between

1 https://www.policyuncertainty.com/energy_uncertainty.html
2 https://www.eia.gov/totalenergy/data/monthly/

3 The time-series of each variable are implicitly assumed to be stationary. Formal tests for a unit root in each series, easily reject the null hypothesis of non-stationarity.

Table 2: Nonlinear Granger causality test for renewable energy consumption based on the renewable energy consumption for the industrial sector index and energy uncertainty index

Lag parameter	CGI	F-value
p=2	Granger causality index	
p=2	3.55E-01	76.8107*** 0.000E+00
p=3	5.45E-01	79.5368*** 2.03E-10
p=6	8.92E-01	74.0324*** 0.000E+00
p=9	8.70E-01	30.6471*** 0.000E+00
p=12	6.20E-01	16.3234*** 1.95E-52
p=18	1.99E-01	2.8731*** 3.15E-14
p=24	3.33E-01	2.2104*** 1.05E-21
p=9	8.40E-02	0.7348 0.9860

This table reports the nonlinear Granger causality test between the Energy Uncertainty Index and industrial-based Renewable Energy Consumption across different lags *p*. The maximum number of lags considered is 32 months. The F-values and the *P* values of the nonlinear Granger causality test are reported. The *P* values of the test are given below in brackets. The null hypothesis is that the Energy Uncertainty Index does not cause Renewable Energy Consumption. □□□, □□ and □ The rejection of the null hypothesis of no-causality at the 1%, 5%, and 10% level, respectively. The Granger causality index (GCI) can be computed as $\log\left(\sigma_1^2 / \sigma_2^2\right)$

Renewable Energy Consumption for the industrial sector and the Energy Uncertainty Index across various lag parameters. Specifically, the Granger causality index (CGI) demonstrates a strong predictive capability for Renewable Energy Consumption at multiple lags, with F-values consistently showing statistical significance at the 1% level (indicated by ***) for lags 2, 3, 6, 9, 12, 18, and 24 and 32.

The most pronounced causal influence is observed at lag 3, with an F-value of 79.5368 and a P = 2.03E-10, suggesting a robust relationship between energy consumption and uncertainty in energy. Similarly, at lag 6, an F-value of 74.0324 and a P = 0.000E+00 reinforce this significant association. This trend suggests that changes in the Energy Uncertainty Index have immediate implications for Renewable Energy Consumption in the industrial sector.

Moreover, as observed in the results for lag 12, the F-value of 16.3234 with a P = 1.95E-52 continues to support the rejection of the null hypothesis of no causality, highlighting the sustained impact of energy uncertainty on consumption patterns over time. However, at longer lags, such as P = 32, the relationship becomes statistically insignificant, as indicated by the P = 0.9860, suggesting that the influence of energy uncertainty on renewable energy consumption diminishes over extended periods.

These findings imply that fluctuations in the Energy Uncertainty Index significantly affect industrial renewable energy consumption in the short to medium term. The immediate impacts are likely driven by how industries adjust their consumption strategies in

Figure 1: This Figure depicts the logarithm of each variable calculated based on monthly data for a sample period covering January 2001 to September 2022. Variable considered are the Energy Uncertainty Index, as well as the Renewable Energy Consumption focusing on the Industrial Sector Index (logarithmic transformation)

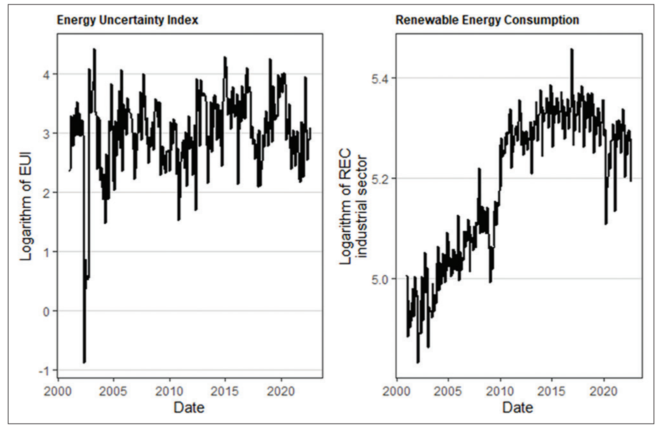
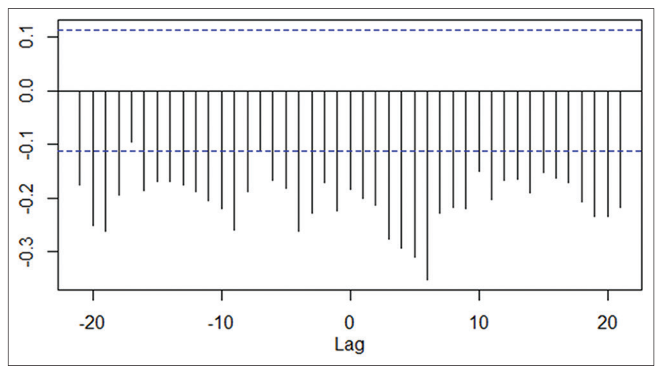


Figure 2: This plot depicts the cross-correlation between the Energy Uncertainty Index and Renewable Energy Consumption (Industrial Sector) for the sample period considered (January 2001 to September 2022)



response to uncertainty in energy supply, reflecting a reactive behavior to external energy market conditions. Over longer time frames, the diminishing causal effect could indicate that industries adapt to uncertainties or develop more stable consumption patterns, reducing the short-term volatility caused by energy supply disruptions. Specifically, the robust causal relationship, particularly at shorter lags, suggests that fluctuations in energy uncertainty exert a critical influence on renewable energy consumption patterns. This aligns with the broader literature indicating that economic policy uncertainty negatively impacts renewable energy uptake. For instance, Ivanovski and Marinucci (2020) found a long-run negative relationship between economic policy uncertainty and renewable energy consumption, emphasizing that increased uncertainty can dampen investments in renewables. Such insights are vital for policymakers aiming to foster energy transitions, as they highlight the need to manage economic risks effectively to encourage the adoption of renewable energy technologies. Moreover, the negative long-term effects of economic policy uncertainty on energy investments, as demonstrated in multiple studies, reinforce the importance of creating stable policy environments to promote sustainable energy initiatives.

Additionally, the implications of this research extend beyond immediate consumption patterns, highlighting the importance of stability in energy policy to ensure the long-term viability of renewable energy initiatives. As noted by Feng and Zheng (2020), the impact of economic policy uncertainty can promote innovation in renewable energy, yet only in contexts where governance quality is high. This suggests that while uncertainty can spur innovation, it can also hinder consistent adoption unless coupled with effective governance structures. Furthermore, Lu et al. (2021) show that in contexts with high economic policy uncertainty, the consumption of renewable energy might experience long-term adverse effects, emphasizing the need for targeted interventions in energy policy. As countries transition to greener economies, understanding these dynamics will be crucial for minimizing risks and maximizing the potential of renewable energy sources. Overall, these insights provide critical guidance for crafting policies that not only address immediate energy needs but also facilitate a sustainable energy future in the face of economic uncertainties.

Overall, the results highlight the importance of monitoring the Energy Uncertainty Index, as it appears to play a critical role in shaping renewable energy consumption behaviors in the industrial sector. This relationship has important implications for policymakers and energy planners seeking to ensure a stable and sustainable energy future, as understanding the dynamics of energy uncertainty can inform strategies to mitigate its impacts on renewable energy usage.

5. CONCLUDING REMARKS

In this study, we employed a nonlinear Granger causality test to investigate the relationship between the Energy Uncertainty Index and Renewable Energy Consumption in the industrial sector. The methodology involved analyzing various lag parameters, ranging from 2 to 32 months, to assess the dynamic interactions between energy uncertainty and renewable energy consumption. By utilizing this advanced econometric approach, we aimed to capture the complexities of causality that may not be evident in traditional linear models. The study's design was motivated by the need to understand how fluctuations in energy uncertainty influence renewable energy adoption, particularly in the context of increasing reliance on sustainable energy sources amid global environmental concerns.

The results from our analysis reveal a robust causal relationship between the Energy Uncertainty Index and Renewable Energy Consumption, particularly at shorter lag intervals. Statistically significant F-values at multiple lags indicated that higher levels of energy uncertainty are associated with decreased renewable energy consumption in the industrial sector. This finding is critical, as it suggests that energy uncertainty can significantly hinder the adoption of renewable technologies, potentially delaying the transition toward more sustainable energy practices. Furthermore, the significance of the causal relationship diminishes at longer lags, indicating that the immediate impacts of energy uncertainty are more pronounced than its long-term effects.

These findings are in line with existing literature that highlights the adverse effects of economic policy uncertainty on renewable energy investments. For instance, previous studies have shown that higher uncertainty levels can lead to reduced investments in renewable technologies, as investors become wary of potential risks associated with unstable policy environments. Our study reinforces this perspective, suggesting that policymakers must address the inherent risks and uncertainties in the energy sector to encourage a more robust adoption of renewable energy sources.

Additionally, the implications of our findings extend beyond immediate consumption patterns, underscoring the necessity for stable and predictable policy frameworks. Economic policy uncertainty not only impacts current renewable energy consumption but may also inhibit long-term investments and innovation in the sector. As indicated by previous research, fostering a stable economic environment is essential for mitigating risks and promoting sustainable energy initiatives. Therefore, policymakers are urged to implement strategies that reduce uncertainty and create conducive conditions for renewable energy investment.

In conclusion, our research contributes to the growing body of research on the interplay between economic uncertainty and renewable energy consumption, providing valuable insights for both scholars and policymakers. By highlighting the significant causal relationships identified through our nonlinear Granger causality analysis, we emphasize the need for informed policy decisions that account for the volatility and uncertainty in the energy landscape. Future research could further explore these dynamics across different sectors and regions to better understand the broader implications for global energy transitions and sustainability efforts.

6. ACKNOWLEDGMENT

This work has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101178789 (EVOSST). Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union. Neither the European Union nor the granting authority can be held responsible for them.

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