energies

MDPI

Article

Transition to Renewable Energy Production in the United States: The Role of Monetary, Fiscal, and Trade Policy Uncertainty

Muhammad Jamil [1], Farhan Ahmed [2], Gouranga Chandra Debnath [3] and Štefan Bojnec [4,*]

[1] Ghulam Ishaq Khan Memorial Chair (SBP), Kashmir Institute of Economics, The University of Azad & Jammu Kashmir, Muzaffarabad 13100, Pakistan; m.jamil@ajku.edu.pk
[2] Department of Economics & Management Sciences, NED University of Engineering & Technology, Karachi 75270, Pakistan; fahmed@neduet.edu.pk
[3] School of Business & Economics, United International University, Dhaka 1212, Bangladesh; gouranga@bus.uiu.ac.bd
[4] Faculty of Management, University of Primorska, SI-6101 Koper-Capodistria, Slovenia
* Correspondence: stefan.bojnec@fm-kp.si or stefan.bojnec@siol.net

Abstract: Renewable energy has emerged as a key to attain higher economic growth without any detrimental impact on the environment. Therefore, the entire world is in the transition phase from non-renewables to renewables. To improve the levels of production of renewable energy, it is inevitable to discern its determinants. Hence, this study aims to probe the impact of monetary, fiscal, and trade policy uncertainty on renewable energy production in the United States. To this end, the novel smooth and sharp structural breaks unit root test is used to scrutinize the order of integration. Next, we also apply the novel augmented autoregressive distributed lag methodology for discerning cointegration. The findings note that, in the long- and short-run, monetary policy uncertainty plunges the production of renewable energy, whereas fiscal policy uncertainty upsurges it. Further, trade policy uncertainty does not affect renewable energy production. Based on these results, we propose policy suggestions that could expedite the transition to renewables.

Keywords: global environment awareness; renewable energy transition; renewable energy production; sustainability; economic policy; unit root test; autoregressive distributed lag model

check for updates

Citation: Jamil, M.; Ahmed, F.; Debnath, G.C.; Bojnec, Š. Transition to Renewable Energy Production in the United States: The Role of Monetary, Fiscal, and Trade Policy Uncertainty. *Energies* **2022**, *15*, 4527. https://doi.org/10.3390/en15134527

Academic Editor: Jin-Li Hu

Received: 8 April 2022
Accepted: 10 May 2022
Published: 21 June 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

There has been an unprecedented upsurge in environmental degradation since the inception of the industrial revolution. As a result, natural disasters and extreme weather events occur frequently nowadays. On top of this, environmental degradation affects the consumption and production behavior of economic agents, as well as causing several human diseases. Hence, curbing environmental degradation is a top-priority agenda of the entire world. It is frequently quoted that greenhouse gases are accountable for abysmal environmental quality, with carbon dioxide (henceforth CO_2) emission being the most critical part of greenhouse gases, having the largest share of the total volume of greenhouse gases. The prime reason behind high CO_2 emissions is human-based production and consumption activities [1]. Industrial production mainly uses non-renewable energy sources as an input, which emits high volumes of CO_2 emissions. Similarly, several consumption activities such as logistics and transport services also utilize energy sources, especially the non-renewable energy sources. Thus, the use of non-renewable energy is one of the culprits behind high CO_2 emissions. Contrarily, non-renewable energy is also subject to several momentous concerns, such as energy insecurity and volatility in energy prices, causing issues in decision-making related to consumption- and production-based activities. Therefore, the entire world is on a quest to seek alternative avenues that can replace non-renewable energy sources. Parallel to this, renewable energy is considered a clean energy source that curbs CO_2 emissions without positing adverse impacts on the

pace of economic growth [2]. Therefore, the entire world is in the transition phase from non-renewable energy to renewable energy. However, there are several factors that act as a hindrance to the development of renewable energy. For instance, the high installation cost, lack of investment in the renewable energy sector, and uncertain economic policies are among the leading factors that discourage renewable energy production. Hence, it is essential to discern the drivers of renewable energy production in order to shape policies that will promote renewable energy generation.

In previous literature, several determinants of renewable energy production have been investigated, such as economic growth [3], price level [4], CO_2 emissions [5], and investment [6], among others. Further, Bourcet [7] provides a literature survey on the determinants of renewable energy production. The author segregates the determinants of renewable energy production into five major categories, i.e., economic, technical, environmental, institutional, and social determinants. However, the prior literature disregards uncertainty in economic policies as a driver of renewable energy production. Economic policy uncertainty has the potential to alter renewable energy production through several channels. One of the channels notes that higher economic policy uncertainty discourages investment, including the investment in renewable energy. Hence, renewable energy production witnesses a plunge over time. On the contrary, economic policy uncertainty can exert pressure on non-renewable energy prices, which in turn plunges the demand for non-renewable energy. As a result, renewable energy production is increased. It is worth noting that economic policy uncertainty can exert both a positive and a negative impact on renewable energy production, therefore, it is indispensable to explore the net impact of economic policy uncertainty on renewable energy production.

On the basis of the aforementioned discussion, the current study aims to discern the impact of economic policy uncertainty on renewable energy production in the United States (US). The present study chooses the US for this analysis as it is the largest economy in the world and the second-largest carbon emitter [8]. Moreover, the US is among the top ten producers of renewable energy. Regarding the energy structure of the US (https://www.eia.gov/energyexplained/us-energy-facts/#:~:text=Total%20energy%20production%20declined%20by,primary%20energy%20production%20in%202020 (accessed on 11 March 2022)), referring Figure 1, on the consumption side, the top energy sources include petroleum (35%), natural gas (34%), renewables (12%), and coal (10%). While the top sectors, in terms of consumption, consist of electric power (35.75 British Thermal Unit—BTU), transportation (24.23 BTU), industrial (22.10 BTU), and the residential sector (6.54 BTU).

Regarding energy production in the US, the top sources comprise natural gas (36%), petroleum (32%), coal (11%), renewable energy (12%), and nuclear energy (9%). Renewable energy (including wind, hydroelectric, solar, biomass, and geothermal energy) is a critical energy source in the US, with a record highest production of 12.31 quads in 2021, which is almost 5% higher compared to the level of production in 2020. Wind and solar energy sources are the main players behind the increasing trend in renewable energy production, whilst biomass and geothermal energy production have also been increasing at a slightly lower rate (See Figure 2).

In the US, 21% of electricity was generated by renewable energy sources in 2020. Followed by natural gas, renewable energy has become the second-largest source of electricity production in the US. Regarding the sources of renewable energy production, wind is the biggest source of REP, followed by hydro-power and solar energy. Figure 3 shows the REP by sources over time (See Figure 3).

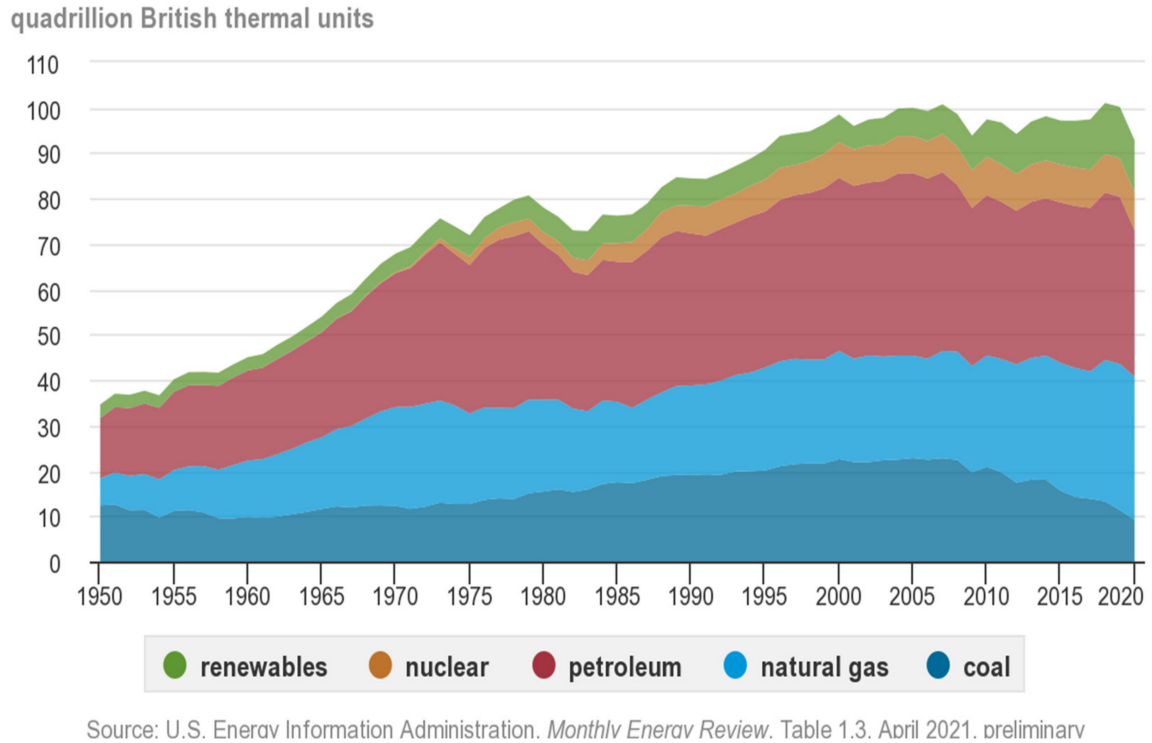


Figure 1. Energy consumption by sources.

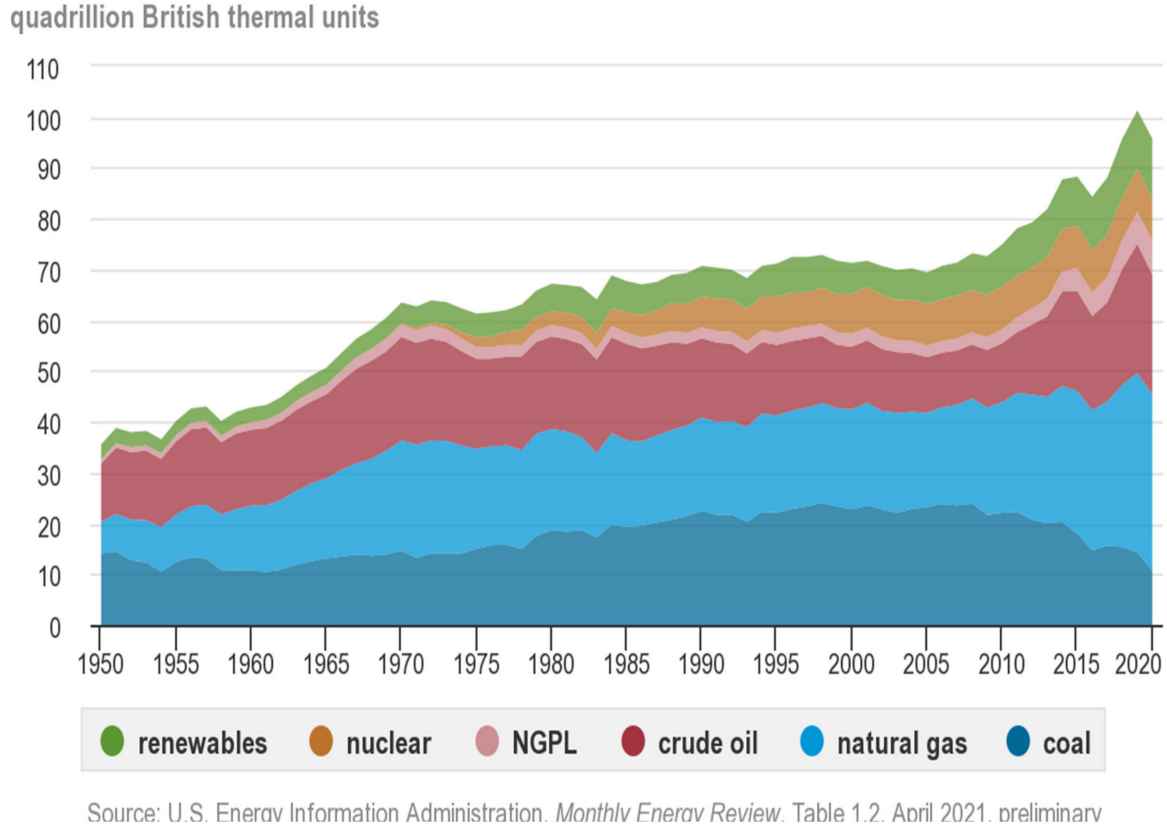


Figure 2. Energy production by sources.

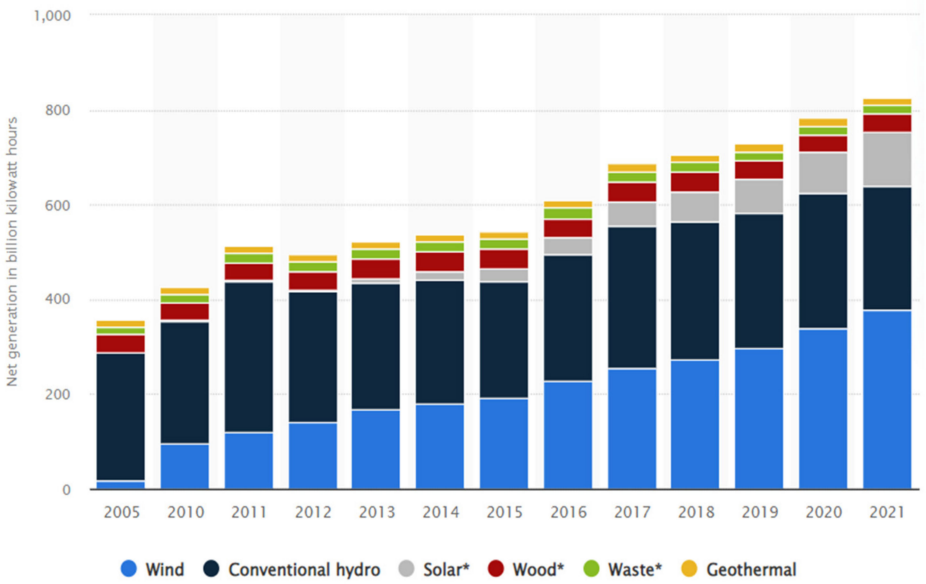


Figure 3. Renewable energy production by source. Asterisk (*) shows the estimated value.

Further, the present study adds to the literature on energy economics in three dimensions. Firstly, this is the first endeavor to link economic policy uncertainty with renewable energy production in the US. It is worth noting that we disaggregate economic policy uncertainty into monetary policy uncertainty, fiscal policy uncertainty, and trade policy uncertainty, in order to explore the separate effect of each policy uncertainty on renewable energy production. Secondly, this study applies the novel smooth and sharp structural breaks unit root test presented by Shahbaz et al. [9], which covers state-dependent nonlinearity coupled with smooth and sharp structural breaks. Thirdly, we employ the novel augmented autoregressive distributed lag methodology, consisting of an additional F-test, and hence provide complete information on cointegration.

Based on the aforesaid arguments, we develop the following null hypotheses:

(1) H_0: monetary policy uncertainty does not affect renewable energy production:
(2) H_0: fiscal policy uncertainty does not affect renewable energy production;
(3) H_0: trade policy uncertainty does not affect renewable energy production.

The rest of the article is organized in the following way. In the next, second section, we provide a literature review. The methods are presented in the third section. The fourth section explains the data. The findings are presented in the fifth section. The final section derives the main conclusions.

2. Literature Review

This section highlights the relevant literature on the determinants of renewable energy production. Drivers of renewable energy production are segmented into five categories such as economic determinants, environmental determinants, institutional determinants, social determinants, and technical determinants [7].

Regarding the economic determinants of renewable energy production, economic growth is an indispensable factor. It is widely reported that economic growth enhances renewable energy production [10,11]. In the case of Iran, it has been concluded that economic growth leads to higher renewable energy production [12]. Similarly, several research studies noted positive co-movements between economic growth and renewable energy production in OECD countries [13]. Thus, we formulate a null hypothesis related to economic growth as:

(4) H_0: economic growth does not affect renewable energy production.

Besides economic growth, energy price and/or general price level is another vital driver of renewable energy production that is extensively explored in the prior body

of knowledge. The rise in energy prices (e.g., oil prices) impedes the demand for non-renewable energy and escalates the demand for renewable energy. As a result, renewable energy production witnessed an upsurge in the economy, remaining in the equilibrium state. Likewise, the higher energy prices of non-renewable energy compel extensive research and development (R&D) investment into the renewable energy sector. Therefore, the production capacity of renewable energy increases over time. In the US, higher electricity prices contribute to higher renewable energy production [14]. For OECD countries, it is noted that inflation enhances renewable energy production [15]. Contrary to this, energy prices do not affect renewable energy production in the OECD countries [16]. Therefore, we develop another hypothesis regarding inflation:

(5) H_0: prices do not affect renewable energy production.

Besides, foreign direct investment is also responsible for higher levels of renewable energy production. In the existing literature, it has been documented that foreign direct investment escalates the REP [17].

Regarding the environmental determinants of renewable energy production, various studies employ CO_2 emissions as an indispensable environmental determinant of REP. As CO_2 emissions could be controlled through the use of renewable energy, several economies expedite renewable energy production based on higher levels of emissions [18]. In Italy, there exists cointegration between CO_2 emissions and renewable energy production [19]. Similarly, causality between CO_2 emissions and renewable energy production has been observed for selected European Union countries [20,21].

It is also worth discussing the technological determinants of renewable energy production. There is a dire need to invest in the R&D of the renewable energy sector in order to produce renewable energy at a low cost. One of the research studies notes that a lack of investment in R&D (i.e., in the renewable energy sector) escalates the cost of renewable energy production, which, in turn, plunges the levels of renewable energy production [22]. In the case of China, there is a positive association between technological advancement in the renewable energy sector and renewable energy production [23].

Next, institutional factors also play a critical role in the production of renewable energy. Government policies can escalate renewable energy production in an economy. It is empirically concluded that a lack of government intervention in the energy market, at a time of market failure, decreases the production of renewable energy [24]. Similarly, the exclusivity of government in the energy sector discourages private firms from entering the market. As a result, renewable energy production is decreased [25]. Several studies employ institutional factors (e.g., institutional quality) as a driver of renewable energy production, and note that renewable energy production depends on these factors [26,27].

Finally, certain studies employ social factors to model renewable energy production. The widely used social determinant of renewable energy production is population. In the prior literature, it has been revealed that population can affect renewable energy production. However, there is no consensus on the net effect of population on renewable energy production [28].

3. Methods

In this study, we use the neoclassical supply function as the empirical model. According to the neoclassical supply function, income and price level escalate the quantity produced. Several studies use this empirical model to explore the determinants of renewable energy production [15]. We incorporate monetary policy uncertainty, fiscal policy uncertainty, and trade policy uncertainty as the key independent variables, and the final empirical model is expressed as follows:

$$REP = f(IPI, CPI, MPU, FPU, TPU) \quad (1)$$

In Equation (1), REP denotes renewable energy production, IPI represents industrial production, and CPI is the consumer price index for energy. Next, MPU describes monetary

policy uncertainty, FPU denotes fiscal policy uncertainty, and TPU is trade policy uncertainty. Following the study of Bhowmik et al. [29], we use IPI as a substitute for GDP, since data on GDP is unavailable. The conceptual model (See Figure 4) is delineated as follows:

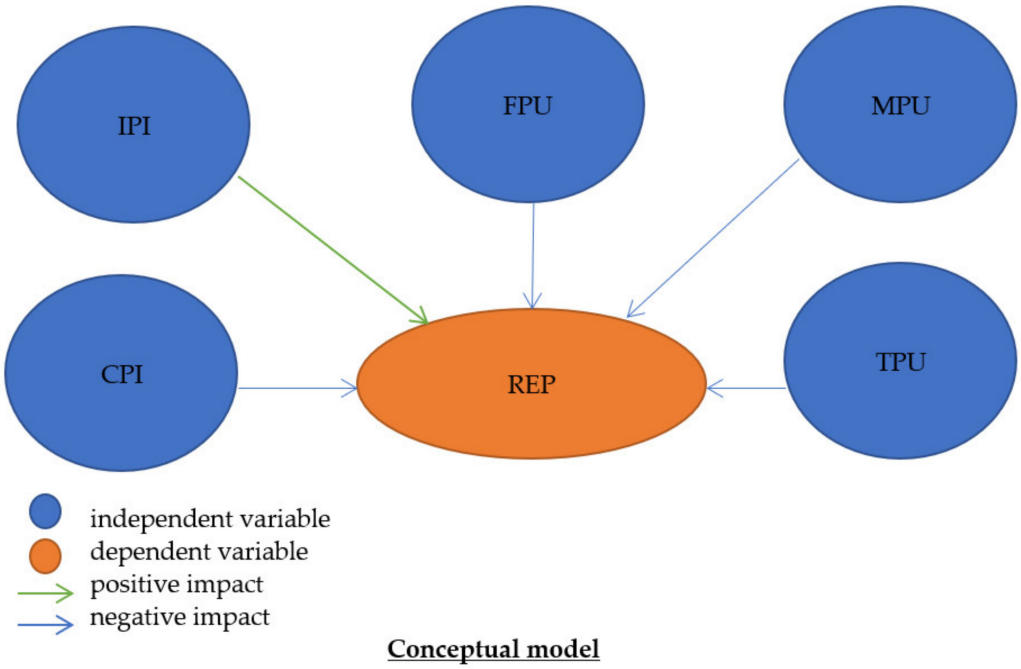


Figure 4. Conceptual Model.

To scrutinize whether MPU, FPU, and TPU affect REP, we employ the novel augmented autoregressive distributed lags (AARDL) model developed by McNown et al. [30] and Sam et al. [31]. To investigate cointegration, Pesaran et al. [32] provide the autoregressive distributed lags (ARDL) bounds test. It is believed that the ARDL bounds test surpasses earlier methods (e.g., Johanson cointegration) as it is applicable even when the variables do not follow the same order of integration [33]. In the ARDL specification, we use the following model/equation in this study:

$$\Delta REP_t = \alpha + \sum_{i=1}^{y} \varphi_i \Delta REP_{t-i} + \sum_{i=0}^{p} \beta_i \Delta MPU_{t-i} + \sum_{i=0}^{q} \gamma_i \Delta CPI_{t-i} + \sum_{i=0}^{m} \omega_i \Delta IPI_{t-i} + \sum_{i=0}^{q_i} \Delta FPU_{t-i} + \sum_{i=0}^{q} \psi_i \Delta TPU_{t-i} + \pi_1 REP_{t-1} + \pi_2 IPI_{t-1} + \pi_3 CPI_{t-1} + \pi_4 MPU_{t-1} + \pi_5 TPU_{t-1} + \pi_6 FPU_{t-1} + v_t \quad (2)$$

Equation (2) delineates case III (i.e., unrestricted intercept with no trend) of the ARDL approach. In Equation (2), α shows the intercept, whereas φ_i, β_i, γ_i, $_i$, ψ_i and ω_i are short-run estimates. Furthermore, π_i (i = 1–6) depicts the long-run estimates. In addition, y, p, q, and m denote the lag order, whilst v_t is the disturbance term. ARDL bounds test assumes that there does not exist any impact of the dependent variable on the explanatory variable(s), implying that the considered variables are (weakly) exogenous. Nonetheless, in real life, the likelihood for this assumption to be fulfilled is low. Thus, if the assumption of weak exogeneity is violated, the assumption regarding the distribution of the bounds test will not be met [30,31].

To confirm the presence of cointegration, Pesaran et al. [32] suggested the following tests: the F-test_1 (H_0: $\pi_1 = \pi_2 = \pi_3 = \pi_4 = \pi_5 = \pi_6 = 0$) on all lagged level variables; and the t-test (H_0: $\pi_1 = 0$) on the lagged level dependent variable.

Nevertheless, McNown et al. [30] and Sam et al. [31] present a supplementary F-test (henceforth F-test_2). The F-test_2 is applied on the lagged level independent variables with the following null hypothesis:

$$H_0: \ \pi_2 = \pi_3 = \pi_4 = \pi_5 = \pi_6 = 0$$

However, in the AARDL approach, F-test_2 is complementary to the aforesaid F-test_1 and *t*-tests by Pesaran et al. [32].

McNown et al. [30] and Sam et al. [31] claim that F-test_1, *t*-test, and F-test_2 should be applied to segregate among (non)cointegration and degenerate cases. There are two degenerate cases (i.e., degenerate case-I and case-II) in ARDL modeling, with both of them inferring that there does not exist any cointegration across the variables. The degenerate case-II is observed if the lagged level dependent variable is found statistically insignificant, whereas degenerate case-I is noticed if the lagged level independent variable(s) are statistically insignificant in the ARDL model. The critical values for the degenerate case-II are offered by Pesaran et al. [32], but the critical values for the degenerate case-I are not provided. To avoid the degenerate case-I, the dependent variable needs to be stationary (I (1)). Nonetheless, unit root tests are eminent for their low power, inferring that their findings could be deceptive. Thus, the novel AARDL test handles this concern with the help of F-test_2. Hence, the AARDL method concludes that co-integration will be scrutinized based on F-test_1, *t*-test, and F-test_2. Additionally, cointegration occurs if we reject the null hypothesis of F-test_1, *t*-test, and F-test_2. Hence, the AARDL approach surpasses conventional ARDL bounds tests, since it expounds a complete picture of cointegration and rules out any inconclusive findings.

4. Data

We make use of monthly data for the US spanning over 1985M1-2020M12 (i.e., 432 observations). Total renewable energy production (REP), which is measured in trillion British Thermal units, is used as a dependent variable. Several studies use REP as a dependent variable to model the determinants of renewable energy production [34]. IPI and CPI are incorporated in the empirical model as the control variables. IPI is measured as levels of industrial production against the base year 2017, while the CPI is measured against the base year 2015. It is worth noting that several studies use CPI to explore its impact on REP [13,15]. The considered independent variables include MPU, FPU, and TPU. These aforementioned indices are measured through the frequency of policy uncertainty-related words in the newspaper article (For details on methodology to measure MPU, FPU, and TPU, refer to Baker et al. (2016).). Recently, several researchers have used these indices to model CO_2 emissions [29]. The data on REP is gathered from Energy Information Administration (EIA), while IPI and CPI are downloaded from Federal Reserve Data (FRED). The data on MPU, FPU, and TPU is gathered from policyuncertainty.com (accessed on 1 February 2022). Next, we converted the entire dataset into the logarithmic format. The descriptive statistics are reported in Table 1, with a description of the variables used in Table A1 in Appendix A. The mean value is the highest for the REP, while it is the lowest for the CPI. Next, the series of TPU has witnessed the highest variation, whilst IPI contains the lowest standard deviation. The entire dataset is positively skewed except CPI, which has negative skewness. Kurtosis, on the other hand, notes that there are not heavy tails in the data series. Finally, the Jarque-Bera test reveals that all variables follow the non-normal distribution, except MPU, which follows the normal distribution.

Table 1. Descriptive Statistics.

Measures	CPI	FPU	MPU	TPU	REP	IPI
Mean	−0.40	4.51	4.36	4.35	6.39	4.42
Std. Dev.	0.85	0.56	0.59	0.93	0.25	0.14
Skewness	−0.81	0.28	0.04	0.51	0.69	0.36
Kurtosis	2.51	2.57	2.63	3.21	2.24	2.26
Jarque-Bera	(0.00) ***	(0.00) ***	(0.28)	(0.00) ***	(0.00) ***	(0.00) ***

Table 1. *Cont.*

Measures	CPI	FPU	MPU	TPU	REP	IPI
Unit of measurement	Indices with the base year 2015	Frequency of newspaper articles containing terms related to FPU	Frequency of newspaper articles containing terms related to MPU	Frequency of newspaper articles containing terms related to TPU	British Thermal units	Level of industrial production with the base year 2017
Source	FRED	Policyuncertainty.com (accessed on 1 February 2022).	Policyuncertainty.com (accessed on 1 February 2022).	Policyuncertainty.com (accessed on 1 February 2022).	EIA	FRED

(.) represents the *p*-value. *** denotes the level of significance at 1%.

5. Results

We follow a four-step methodology in our analysis, which is delineated in Figure 5 below.



Figure 5. Steps to be followed in methodology.

In the first step, we probe the order of integration using Augmented Dickey Fuller (ADF) and smooth and sharp structural breaks (SOR) tests. The findings from unit root testing help us to choose an appropriate methodology for cointegration testing. The next step is about testing cointegration using the AARDL bounds test, which reports whether there exists any long-run association among selected variables. In the third step, we estimate the long- and short-run coefficients using the AARDL model. Finally, we perform sensitivity analysis by comparing our baseline findings with the results of the Fully Modified Ordinary Least Square (FMOLS), Dynamic Ordinary Least Square (DOLS), and Canonical Cointegrating Regression (CCR).

5.1. SOR Unit Root Test

It is inevitable to discern the existence of unit root in order to choose the appropriate methodology, otherwise, the inappropriate methodology may lead to spurious outcomes [35]. Existing literature provides several unit root tests, with the augmented Dickey-Fuller (ADF) test being the most widely used traditional unit root test. However, the traditional unit root tests do not cover several types of structural breaks. Moreover, these tests do not cover smooth and sharp structural breaks in consort with state-dependent nonlinearity at the same time. To cover these issues the novel SOR unit root test has recently been presented by Shahbaz et al. [9], which covers smooth and sharp structural breaks with the consort of state-dependent nonlinearity. It is worth reporting that the novel SOR test uses Fourier transformation, which does not require prior information on the number and nature of structural breaks. Thus, we use the ADF test coupled with the novel SOR unit root test in this analysis.

Table 2 presents the findings from the ADF test. At I (0), we are unable to reject the null hypothesis (henceforth H_0) of no unit root for the entire dataset except for FPU, wherein we can reject H_0. Thus, we conclude that FPU is integrated at I (0). Next, we can reject H_0 at I (1) for all other variables (i.e., IPI, CPI, REP, MPU, and TPU) and hence report that all other variables are following I (1).

Table 2. ADF Test.

Variable	I (0)	I (1)
IPI	(0.11)	(0.00) ***
CPI	(0.21)	(0.00) ***
REP	(0.14)	(0.00) ***
MPU	(0.17)	(0.00) ***
FPU	(0.01) **	-
TPU	(0.13)	(0.00) ***

(.) denotes *p*-value. *** denotes the level of significance at 1%, whilst ** represents it at 5%.

Next, Table 3 reports findings from the novel SOR unit root test. For the SOR test, H_0 claims that the unit root exists in the data, and the alternate assumes otherwise. In the case of IPI, we could reject the H_0 at I (0) for all models because the calculated test statistics are greater than the critical values. This implies that IPI does not contain unit root at I (0). On the contrary, H_0 could not be rejected at I (0) in all models for MPU, FPU, TPU, REP, and CPI. This indicates that these aforementioned variables are not integrated at I (0). However, we can reject H_0 for these aforesaid variables at the first difference, inferring that these variables follow I (1).

Table 3. SOR Test.

Indicator	I (0)			I (1)		
Measure	**Model_AA**	**Model_BB**	**Model_CC**	**Model_AA**	**Model_BB**	**Model_CC**
REP	−2.814	−3.16	−3.47	−4.89 **	−4.99 **	−5.88 **
CPI	−2.02	−2.11	−2.14	−6.56 **	−6.75 **	−6.92 **
IPI	−3.90 **	−3.60 **	−2.67 **	–	–	–
MPU	−2.54	−2.64	−3.01	−5.59 **	−5.98 **	5.99 **
TPU	−2.50	−2.24	−3.00	−5.69 **	−5.99 **	6.19 **
FPU	−1.54	−1.64	−3.11	−6.19 **	−6.99 **	7.13 **

** represents *p*-value < 0.05. The authors' set the frequency at 5. The critical values are gathered from Table 2 of Shahbaz et al. [9]. Model_AA, Model_BB, and Model_CC describe a model with intercept, with slope, and with slope & intercept, respectively.

5.2. AARDL Bounds Test

We employ the novel AARDL bounds test to validate the cointegration among the considered variables. It is worth noting that cointegration is defined as the presence of the long-run association among the selected variables. As depicted in Table 4, the calculated values from all three tests are greater than the upper bound critical values. Thus, we can reject H_0 of no cointegration, and hence document that long-run association holds in our analysis.

Table 4. AARDL Bounds Test.

Test	Calculated Value	Lower Bound	Upper Bound
F-test_1	7.14 ***	3.41	4.68
t-test	−5.28 ***	−3.43	−4.79
F-test_2	9.75 ***	3.05	5.02

The critical values for F-test (2) are gathered from Sam et al. [31]. *** shows *p*-value < 0.01.

5.3. Short- and Long-Run Elasticities

This sub-section provides the short- and long-run estimates retrieved from the novel AARDL model. Regarding the long-run findings, MPU is statistically significant and contains a negative sign. This implies that MPU plunges the REP in the US. The value of MPU is −0.17, indicating that a 1% increase in MPU impedes the REP by 0.17%. The reason behind this outcome could be that the MPU discourages investment (especially in

RE projects), which in turn mitigates REP. Moreover, MPU could posit adverse impacts on EG which eventually decreases REP. Next, FPU is statistically significant and contains a positive sign, indicating that FPU escalates REP. The coefficient of FPU is 0.21, implying that a 0.21% upsurge in REP is fostered by a 1% increase in FPU. There is a likelihood that FPU escalates the concern related to future NRE prices due to an increase/decrease in taxes causing investment costs. As a result, the economy can switch from NRE to RE. Further, TPU is statistically insignificant. This infers that TPU does not affect REP in the long-run.

Regarding the long-run results of the control variables, IPI is statistically significant with a positive sign, reporting that industrial production also improves REP in the US. This evidences that industrial production leads to higher EG. As a result of higher income, REP can increase. This finding is consistent with the study [36], and the outcome is also backed by the study [37]. Also, CPI is statistically insignificant, indicating that inflation does not explain REP in the economy. Similar results are also documented by Gan and Smith [13] and Chang et al. [15], who reported that CPI for energy does not affect REP.

Regarding the short-run estimates, MPU is statistically significant with a negative sign, indicating that MPU plunges the REP. The coefficient of MPU is −0.01, inferring that a 1% increase in MPU impedes the REP by 0.01%. Next, FPU is statistically significant and contains a positive sign, noting that FPU leads to higher REP. The magnitude of FPU is 0.02, reporting that a 0.02% increase in REP is fostered by a 1% increase in FPU. Interestingly, TPU is statistically insignificant, revealing that REP does not depend on TPU. Regarding the control variables, in the short-run, IPI is positive and statistically significant, inferring that IPI contributes to higher REP. While CPI is statistically insignificant, demonstrating that inflation does not affect REP.

The last section of Table 5 reports the diagnostics. The error correction term (ECT) explains the speed of adjustment. The coefficient of ECT is −0.18, and it is also statistically significant. This implies that any deviation from long-run equilibrium is corrected by 18% each month. The Durbin-Watson test statistic shows that there is not an issue of serial correlation in the model as its value is close to 2 (i.e., a benchmark for the Durbin-Watson statistic). The Lagrange multiplier (LM) test statistic also concludes the same findings: that there is no issue of serial correlation in this model. The Auto-Regressive Conditional Heteroskedasticity (ARCH) test concludes that heteroskedasticity is not present in the model. Finally, the cumulative sum control chart (CUSUM) and CUSUM-square note that the estimated model is stable. Figures 6 and 7 also depict the graphical representation of CUSUM and CUSUM-square tests.

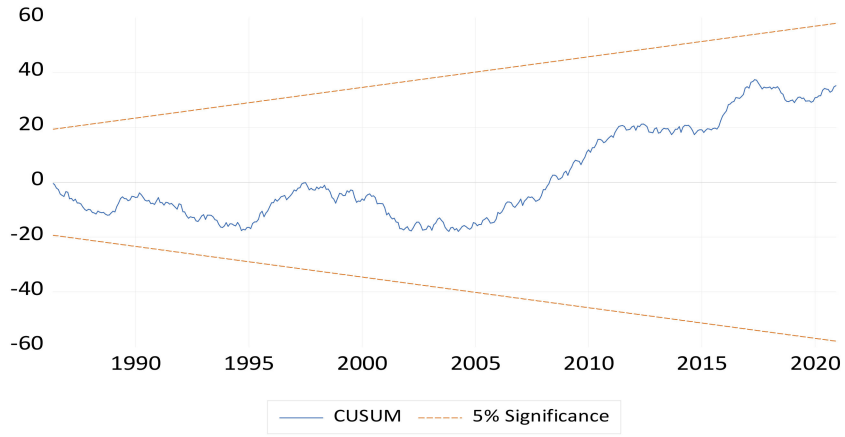


Figure 6. CUSUM Test.

Table 5. Short- and Long-Run Results.

Variable	Coefficient	*p*-Value
Long-Run Estimates		
MPU	−0.17 ***	0.00
FPU	0.21 ***	0.00
TPU	0.03	0.16
IPI	1.61 ***	0.00
CPI	−0.06	0.16
Short-Run Estimates		
MPU	−0.01 **	0.03
FPU	0.02 ***	0.00
TPU	0.01	0.13
IPI	0.43 ***	0.00
CPI	−0.01	0.10
Diagnostics		
ECT	−0.18 ***	0.00
Durbin-Watson	1.96	
LM test	-	0.23
ARCH test	-	0.19
CUSUM	Stable	
CUSUM-square	Stable	

*** denotes *p*-value < 0.01. ** denotes *p*-value < 0.05. We do not report the short-run coefficients at higher lags. ECT represents the error correction term.

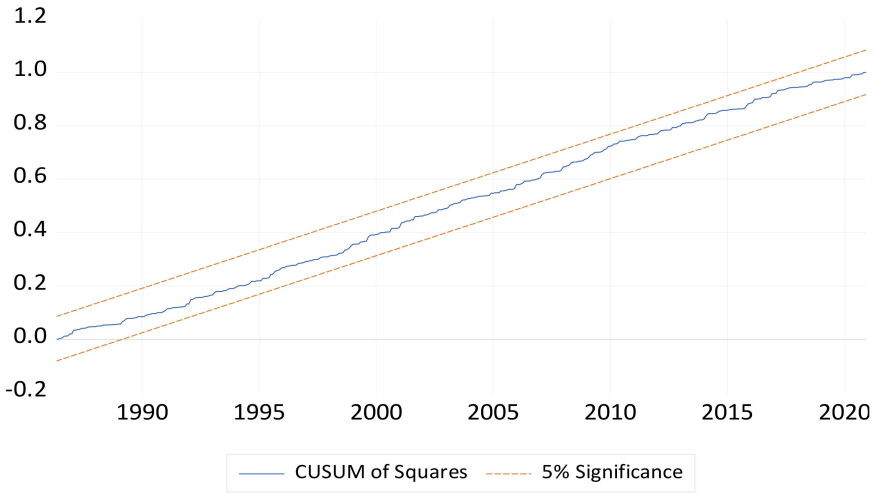


Figure 7. CUSUM-Square Test.

In Figures 6 and 7, the red dotted line shows the level of significance at 5%, while the blue line reflects the calculated CUSUM statistic over time. Since the blue line lies between the red lines, we can conclude that the estimated model is stable.

Finally, we note that hypotheses 1, 2, and 4 can be rejected, because MPU, FPU, and IPI do affect REP, respectively. On the contrary, hypotheses 3 and 5 could not be rejected because TPU and CPI are found to be statistically insignificant.

5.4. Sensitivity Analysis

Authors have employed Fully Modified Ordinary Least Square (FMOLS), Dynamic Ordinary Least Square (DOLS), and Canonical Cointegrating Regression (CCR) for sensitivity analysis to discern whether the findings are sensitive to the methodology. The findings are reported in Table 6. MPU is negative and statistically significant in all models (i.e., FMOLS, DOLS, and CCR). This implies that MPU plunges the REP in the long run. Next, FPU is statistically significant and contains a positive sign across all models. This indicates that

FPU encourages REP. Moreover, TPU is statistically insignificant, showing that REP does not depend on TPU. Regarding the control variables, IPI is statistically significant with a positive sign. This infers that IPI escalates the REP. On the contrary, CPI is insignificant, highlighting that REP does not depend on CPI. It is worth noting that the findings from FMOLS, DOLS, and CCR are similar to the outcomes from the novel AARDL. Hence, we could conclude that the findings are not sensitive to the choice of methodology.

Table 6. FMOLS, DOLS, and Canonical Cointegrating Regression (CCR).

Variable	FMOLS	DOLS	CCR
MPU	−0.10 ***	−0.13 ***	−0.11 ***
FPU	0.14 ***	0.15 ***	0.14 ***
TPU	0.02	0.01	0.02
IPI	1.68 ***	1.64 ***	1.69 ***
CPI	−0.07	−0.07	−0.08

*** p-value < 0.01.

6. Conclusions

Renewable energy is one of the avenues that can lead to a higher EG without positing an abysmal impact on environmental quality. Hence, the entire world is in the transition phase of switching from NRE to RE. However, the share of RE is still remarkably low in the total energy mix, calling for research-backed policy interventions. Therefore, it is inevitable to explore the determinants of REP in order to devise future policies for sustainable development. Therefore, the current study explores the impact of MPU, FPU, and TPU on REP in the US using monthly data. We use the novel SOR unit root test to discern the stationarity of the dataset. The findings reveal that the considered variables are integrated either at I (0) or I (1). Further, we employ the novel AARDL model to probe the cointegration. The findings from the novel AARDL model document that MPU plunges the REP in the long- and short-run. On the contrary, FPU escalates the REP across the short- and long-run. Finally, TPU does not explain TPU either in the short- or long-run. On top of this, we use FMOLS, DOLS, and CCR methodology for sensitivity analysis. The findings from these aforementioned models are also in line with the baseline findings retrieved from the novel AARDL model.

We can propose various policy implications based on our findings. First, the US should formulate policies to escalate industrial production/EG which in turn upsurges the REP. Policymakers can facilitate the industrial sector through tax exemptions and subsidies which will escalate industrial production, and the levels of REP will hence ultimately witness an upsurge. Moreover, during the time of low IPI/EG, policymakers need to protect renewable energy producers by introducing special funds for them. Next, since CPI does not affect REP, policymakers should not increase the levels of CPI to compel individuals to switch to renewables. On top of this, renewable energy producers should not make decisions (i.e., related to an increase or decrease in the volume of production) with CPI in mind, because CPI does not affect REP. Third, as MPU discourages REP, policymakers need to shrink the MPU in order to enhance the REP. For this purpose, policymakers should introduce MPU for a relatively long time span. Next, it is well known that monetary policy is launched either through "rule" or "discretion". To control the uncertainty in monetary policy, rule should be adopted instead of discretion. It is a point to note that adverse impacts of MPU on REP are profound in the long-run. Therefore, policymakers need to pay more attention to formulating policies that control MPU hikes in the long-run. Furthermore, special incentives in terms of feed-in-tariff, subsidies, and sales tax exemptions should be given to manufacturers of renewable energy products, at the time of high MPU, to offset the adverse impact of MPU on REP. Next, policymakers should launch special financing schemes for renewable energy markets, which might weaken the adverse impact of MPU on REP. Moreover, since FPU and REP have a positive relationship between them, higher REP is achievable at the cost of higher FPU. Parallel to this, FPU has adverse

economic impacts. Therefore, policymakers also try to control FPU. Thus, additional measures should be taken to enhance REP while keeping the FPU low. For this purpose, policymakers should announce special schemes and policies at the time of low FPU, such as loans with lower interest rates, and imports of renewable energy technologies at lower tariff rates. Since uncertainty relating to future taxation and government expenditures affect the current production decision in renewable energy markets, policymakers should incorporate this fact when formulating energy policies. Most importantly, monetary, fiscal, and energy policies should be in line with each other, in the sense that the core objective of these policies should be the same. For instance, monetary and fiscal policies should also promote/facilitate renewable energy in consort with achieving price stability. Next, since TPU does not affect REP, any policy to shrink TPU will not exert a detrimental impact on REP. Therefore, policymakers should shape policies to shrink TPU since it has adverse economic impacts.

Author Contributions: Conceptualization, M.J. and F.A.; methodology, G.C.D.; software, M.J.; validation, Š.B., F.A. and G.C.D.; formal analysis, M.J.; investigation, F.A.; resources, Š.B.; data curation, F.A.; writing—original draft preparation, M.J. and G.C.D.; writing—review and editing, Š.B.; visualization, G.C.D.; supervision, F.A.; project administration, M.J.; funding acquisition, Š.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used in this study is in the public domain, and the relevant sources are cited in the text. The data can be provided at a reasonable request from the corresponding author.

Acknowledgments: Authors would like to thank Development, Policy, Practice and Research Center (DPPRC) Pakistan for their technical support in completing this study.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Description of variables.

Variable	Acronym	Measurement Scale	Proxy	Definition
Renewable energy production	REP	British Thermal Unit (https://www.eia.gov/energyexplained/units-and-calculators/british-thermal-units.php#:~:text=A%20British%20thermal%20unit%20(Btu,(approximately%2039%20degrees%20Fahrenheit), accessed on 1 February 2022	-	REP is defined as the amount of energy produced through renewable energy sources.
Industrial production	IPI	Level of production against the base year 2017	Industrial production index (As mentioned earlier, IPI is used as a proxy for GDP because the monthly data on GDP is unavailable.)	IPI is a measure of real production/output in the mining, electric, gas, and manufacturing industry, relative to a base year.

Table A1. *Cont.*

Variable	Acronym	Measurement Scale	Proxy	Definition
Inflation	CPI	Level of prices against the base year 2015	Consumer price index	CPI is a measure of the average price change of goods and services purchased by households.
Monetary policy uncertainty	MPU	Number/frequency of words that capture information relating to monetary policy uncertainty, in newspaper articles	Monetary policy uncertainty index	MPU is uncertainty, volatility, or risk related to monetary policy.
Fiscal policy uncertainty	FPU	Number/frequency of words that capture information relating to fiscal policy uncertainty, in newspaper articles	Fiscal policy uncertainty index	FPU is uncertainty, volatility, or risk related to monetary policy.
Trade policy uncertainty	TPU	Number/frequency of words that capture information relating to trade policy uncertainty, in newspaper articles	Trade policy uncertainty index	TPU is uncertainty, volatility, or risk related to monetary policy.

References

1. Hashmi, S.M.; Bhowmik, R.; Inglesi-Lotz, R.; Syed, Q.R. Investigating the Environmental Kuznets Curve hypothesis amidst geopolitical risk: Global evidence using bootstrap ARDL approach. *Environ. Sci. Pollut. Res.* **2022**, *29*, 24049–24062. [CrossRef]
2. Li, X.; Ozturk, I.; Syed, Q.R.; Hafeez, M.; Sohail, S. Does green environmental policy promote renewable energy consumption in BRICST? Fresh insights from panel quantile regression. *Econ. Res.-Ekon. Istraživanja* **2022**. [CrossRef]
3. Aguirre, M.; Ibikunle, G. Determinants of renewable energy growth: A global sample analysis. *Energy Policy* **2014**, *69*, 374–384. [CrossRef]
4. Bengochea, A.; Faet, O. Renewable energies and CO_2 emissions in the European Union. *Energy Sources Part B Econ. Plan. Policy* **2012**, *7*, 121–130. [CrossRef]
5. Przychodzen, W.; Przychodzen, J. Determinants of renewable energy production in transition economies: A panel data approach. *Energy* **2019**, *191*, 116583. [CrossRef]
6. Romano, A.; Scandurra, G. Investments in renewable energy sources in OPEC members: A dynamic panel approach. *Adv. Methodol. Stat.* **2014**, *11*, 93–106. [CrossRef]
7. Bourcet, C. Empirical determinants of renewable energy deployment: A systematic literature review. *Energy Econ.* **2020**, *85*, 104563. [CrossRef]
8. Syed, Q.R.; Bouri, E. Impact of economic policy uncertainty on CO_2 emissions in the US: Evidence from bootstrap ARDL approach. *J. Public Aff.* **2021**, e2595. [CrossRef]
9. Shahbaz, M.; Omay, T.; Roubaud, D. Sharp and smooth breaks in unit root testing of renewable energy consumption. *J. Energy Dev.* **2018**, *44*, 5–40.
10. Apergis, N.; Payne, J.E. The causal dynamics between renewable energy, real GDP, emissions and oil prices: Evidence from OECD countries. *Appl. Econ.* **2014**, *46*, 4519–4525. [CrossRef]
11. Apergis, N.; Payne, J.E. Renewable energy, output, CO_2 emissions, and fossil fuel prices in central America: Evidence from a nonlinear panel smooth transition vector error correction model. *Energy Econ.* **2014**, *42*, 226–232. [CrossRef]
12. Khoshnevis Yazdi, S.; Shakouri, B. Renewable energy, nonrenewable energy consumption, and economic growth. *Energy Sources Part B Econ. Plan. Policy* **2017**, *12*, 1038–1045. [CrossRef]
13. Njoh, A.J. A systematic review of environmental determinants of renewable energy performance in Ethiopia: A PESTECH analysis. *Renew. Sustain. Energy Rev.* **2021**, *147*, 111243. [CrossRef]
14. Bird, L.; Bolinger, M.; Gagliano, T.; Wiser, R.; Brown, M.; Parsons, B. Policies and market factors driving wind power development in the United States. *Energy Policy* **2005**, *33*, 1397–1407. [CrossRef]
15. Chang, T.H.; Huang, C.M.; Lee, M.C. Threshold effect of the economic growth rate on the renewable energy development from a change in energy price: Evidence from OECD countries. *Energy Policy* **2009**, *37*, 5796–5802. [CrossRef]
16. Gan, J.; Smith, C.T. Drivers for renewable energy: A comparison among OECD countries. *Biomass Bioenergy* **2011**, *35*, 4497–4503. [CrossRef]

17. Gallagher, K.P.; Zarsky, L. *The Enclave Economy: Foreign Investment and Sustainable Development in Mexico's Silicon Valley*; MIT Press: London, UK, 2007.
18. Da Silva, P.P.; Cerqueira, P.A.; Ogbe, W. Determinants of renewable energy growth in Sub-Saharan Africa: Evidence from panel ARDL. *Energy* **2018**, *156*, 45–54. [CrossRef]
19. Bento, J.P.C.; Moutinho, V. CO_2 emissions, non-renewable and renewable electricity production, economic growth, and international trade in Italy. *Renew. Sustain. Energy Rev.* **2016**, *55*, 142–155. [CrossRef]
20. Dogan, E.; Seker, F. Determinants of CO_2 emissions in the European Union: The role of renewable and non-renewable energy. *Renew. Energy* **2016**, *94*, 429–439. [CrossRef]
21. Vural, G. Analyzing the impacts of economic growth, pollution, technological innovation and trade on renewable energy production in selected Latin American countries. *Renew. Energy* **2021**, *171*, 210–216. [CrossRef]
22. Kutan, A.M.; Paramati, S.R.; Ummalla, M.; Zakari, A. Financing renewable energy projects in major emerging market economies: Evidence in the perspective of sustainable economic development. *Emerg. Mark. Financ. Trade* **2018**, *54*, 1761–1777. [CrossRef]
23. Zhao, Z.Y.; Chen, Y.L.; Li, H. What affects the development of renewable energy power generation projects in China: ISM analysis? *Renew. Energy* **2019**, *131*, 506–517. [CrossRef]
24. Painuly, J.P. Barriers to renewable energy penetration; a framework for analysis. *Renew. Energy* **2001**, *24*, 73–89. [CrossRef]
25. Jacobsson, S.; Bergek, A. Transforming the energy sector: The evolution of technological systems in renewable energy technology. *Ind. Corps Chang.* **2004**, *13*, 815–849. [CrossRef]
26. Romano, A.A.; Scandurra, G.; Carfora, A.; Fodor, M. Renewable investments: The impact of green policies in developing and developed countries. *Renew. Sustain. Energy Rev.* **2017**, *68*, 738–747. [CrossRef]
27. Marques, A.C.; Fuinhas, J.A. Are public policies towards renewables successful? Evidence from European countries. *Renew. Energy* **2012**, *44*, 109–118. [CrossRef]
28. Pfeiffer, B.; Mulder, P. Explaining the diffusion of renewable energy technology in developing countries. *Energy Econ.* **2013**, *40*, 285–296. [CrossRef]
29. Bhowmik, R.; Syed, Q.R.; Apergis, N.; Alola, A.A.; Gai, Z. Applying a dynamic ARDL approach to the Environmental Phillips Curve (EPC) hypothesis amid monetary, fiscal, and trade policy uncertainty in the USA. *Environ. Sci. Pollut. Res.* **2021**, *29*, 14914–14928. [CrossRef]
30. McNown, R.; Sam, C.Y.; Goh, S.K. Bootstrapping the autoregressive distributed lag test for cointegration. *Appl. Econ.* **2018**, *50*, 1509–1521. [CrossRef]
31. Sam, C.Y.; McNown, R.; Goh, S.K. An augmented autoregressive distributed lag bounds test for cointegration. *Econ. Model.* **2019**, *80*, 130–141. [CrossRef]
32. Pesaran, M.H.; Shin, Y.; Smith, R.J. Bounds testing approaches to the analysis of level relationships. *J. Appl. Econ.* **2001**, *16*, 289–326. [CrossRef]
33. Narayan, P. *Reformulating Critical Values for the Bounds F-Statistics Approach to Cointegration: An Application to the Tourism Demand Model for Fiji (Vol. 2, No. 04)*; Monash University: Melbourne, Australia, 2004.
34. Bayale, N.; Ali, E.; Tchagnao, A.F.; Nakumuryango, A. Determinants of renewable energy production in WAEMU countries: New empirical insights and policy implications. *Int. J. Green Energy* **2021**, *18*, 602–614. [CrossRef]
35. Phillips, P.C.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [CrossRef]
36. Bojnec, Š.; Papler, D. Economic efficiency, energy consumption and sustainable development. *J. Bus. Econ. Manag.* **2011**, *12*, 353–374. [CrossRef]
37. Best, R. Switching towards coal or renewable energy? The effects of financial capital on energy transitions. *Energy Econ.* **2017**, *63*, 75–83. [CrossRef]