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Effects of Technology, Energy, Monetary, and Fiscal Policies on the Relationship between Renewable and Fossil Fuel Energies and Environmental Pollution: Novel NBARDL and Causality Analyses

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Abstract: There is a body of research that focuses on the examination of long-run relations between energy–environment–economic growth, and there is also a new type of recent research that focuses on the effects of monetary and fiscal economic policies on the environment. There is a research gap that exists due to omitting the effects of technology and energy policies, and this paper addresses this gap, in addition to merging both fields mentioned above, by including the asymmetric effects of fiscal and monetary policies. To explore the relations between fossil fuel and renewable energies, environmental pollution, and economic growth, in addition to including the roles of energy, technology, monetary, and fiscal policies, this paper employs novel NBARDL and NBARDL Granger Causality methods for yearly data assessments in the USA. The empirical findings of the paper point to the asymmetric impacts of monetary and fiscal policies in the short- and long-run. Interestingly, both contractionary and expansionary fiscal policies lead to higher CO_2 emissions. Contractionary monetary policies exert a downward pressure on CO_2 emissions, and if expansionary, the monetary policy causes environmental degradation. As an important policy, the energy policy emerges as a potent tool for reducing carbon emissions through not only renewable energy, but as a greater impact through energy efficiency and technology. Therefore, this paper highlights the importance of technology policies exhibiting varying relationships with environmental pollution, featuring unidirectional or bidirectional causality patterns. Renewable energy, energy efficiency combined with adequate technology, and energy policies are determined to have pivotal roles in CO_2 emissions outcomes. Such policies should focus on cleaner energy sources accompanied by energy efficiency technologies in the USA to curtail environmental impacts; technology policies are vital in fostering innovations and encouraging cleaner technologies. The policy recommendations include an effective combination of monetary, fiscal, technology, and energy policies, backed by a strong commitment to achieving energy efficiency and renewable energy to mitigate environmental pollution and to contribute to sustainable development.

Keywords: environmental pollution; energy; renewable energy; monetary policy; fiscal policy; energy policy; technology policy; economic growth; causality; nonlinearity; BARDL

1. Introduction

Global environmental problems, such as rising temperatures and weather abnormalities, are increasing throughout the world. The Intergovernmental Panel on Climate Change (IPCC) reported in 2021 and 2023 that the worldwide surface temperature increased by

1.1 °C in the periods of 1850–1900 and 2011–2020, causing global warming to reach unprecedented levels [1,2]. This global warming is due to greenhouse gases (GHGs), dominated mainly by carbon dioxide (CO_2), followed by methane (CH_4) [1]. The CO_2 concentrations in the atmosphere were 410 parts per million (ppm), while the concentration of CH_4 was 1866 parts per billion (ppb) and nitrous oxide (N_2O) was 332 ppb in 2019 [2], and these levels were the highest for CH_4 and N_2O in the past 800,000 years, and the highest for CO_2 in the past two million years. The IPCC report warned that global CO_2 emissions were making a sharp incline, which increased after the 1950s and underlined the need for urgent action [2]. These reports led to the questioning of the commitment of nations to take the necessary steps to prevent a crisis. As a seminal and historical agreement in this direction, the Kyoto protocol [3] was signed 2.5 decades ago, and given these figures mentioned above, it is clear that there has been no drastic reduction in the acceleration rate of GHGs, such as CO_2, leading us to question the level of commitment by the nations towards global warming [4]. Whatever the case, the incline in emissions dramatically accelerated in recent years. Such unprecedented levels of GHG emissions have caused great concerns for environmental sustainability in the near future and the need for immediate action. The increase in CO_2 emissions in 2021 was the highest in history with a total of 2 billion tons [5]. Recent factors that contributed to this acceleration included adverse weather situations due to ongoing climate change, energy market conditions, political disputes due to the Ukrainian war, and no significant reduction in fossil fuel-based energy sources.

Similar to recent years, energy production using fossil fuels remained the primary driver of CO_2 emissions throughout the century [5]. To date, coal satisfies a large share of the energy demand, 15.3b tons, accounting for more than 40% of global CO_2, followed by 10.7 tons of global CO_2 coming from oil and transportation activities, and 7.5b tons from natural gas [5]. Fossil fuel-based energy consumption and the factors leading to the increase in primary energy are the subject of many studies. In thisliterature, the effects of policy implementations are under special consideration; for a relevant review, we refer the readers to [6]. Many studies discuss the effects of the fiscal policy (FP) and monetary policy (MP) in detail, including the fluctuations in interest rates, applications of tax policies, and how they affect energy consumption and environmental pollution levels in addition to other effects. The literature scrutinizes how the expansionary economic policies that favor economic growth have important effects on accelerating the emissions of CO_2, considered among the main GHGs [6]. Such positive effects also exist for contractionary policies. In response to the contractionary monetary policy, for instance, industrialists prefer to use conventional technologies instead of green investments for the production process, and an increase in the use of less environmentally friendly technologies causes environmental pollution and inclines in CO_2 emissions. Conversely, FP instruments are directly and indirectly linked to environmental quality and total energy consumption. Changes in government spending habits transform FPs into expansionary FPs or contractionary FPs. The expansionary FP, in addition to increasing economic growth, also accelerates fossil fuel use and, therefore, the emissions of CO_2 [7–10].

The importance of green taxes with tax incentives applied in line with the quality of the environment is strongly emphasized [10,11]. Some papers explore the environmental-quality-enhancement effects of fiscal decentralization. Fiscal decentralization leads to improved resource allocations by increasing the effectiveness of public expenditures [12]. Additionally, it is worth noting that larger public sectors and administrative and regulatory delays tend to contribute to higher CO_2 emissions from economic activities [13]. Cheng et al. stressed fiscal decentralization and its effect on improving environmental quality [12]. In addition to the FP, a set of papers examined the connection among the MP and environmental degradation [8,13,14]. We further show in the Literature Review Section that an important feature of these studies is to embrace supplementary variables in the empirics. A simultaneous analysis of the MP and FP also presents the important aspects of the policies, including the dynamic effects among the policy types analyzed and the environmental variables, such as the emissions of CO_2 [13,15].

In the studies mentioned, the impacts of energy and technology policies are not considered. Energy and technological policies have important impacts on energy consumption levels and, in return, on environmental policies. In the literature, energy policies are used as policy recommendations; however, these policies also have important impacts on environmental pollution and energy consumption levels. Energy efficiency and technological policies also have important implications for the use of energy and the environmental degradation under the influence of progresses in energy and technology policies, as well as economic policies.

In contrast, alternative energy types, specifically the use of renewable energies, are important for overcoming environmental degradation. The measurements of the level of non-renewable energy consumption (NREN) and the levels achieved due to the use of renewable energies represent the energy policies in an economy. In addition to the levels of consumption of renewable energy (REN) and NREN, a more efficient use of energy, measured with efficiency, represents the energy technology policies that appear as a third factor. In addition, these factors have crucial effects on the environment and are considered as the three pillars of energy policies. At this point, it should be noted that the generation of renewable energy is under the influence of government policies and its production is related to the monetary policy through investments and bank-lending channels [16]. Furthermore, it is also related to the FP through taxation [17]. Although the relevant literature establishes the links of the MP and FP to the environment, it does not emphasize how different energy types are also important. Moreover, the importance of energy efficiency and technology policies are overlooked, especially in the empirical environment and sustainable development literature.

In this study, we simultaneously analyze the nexus amid renewable and fossil fuel energy consumption activities, energy efficiency, technology and energy policies, technology patents, and FP and MP instruments on environmental pollution in 1972–2022 in the USA by using the bootstrapping augmented version of a nonlinear autoregressive distributed lag model, a nonlinear bootstrapping autoregressive model (NBARDL), and the nonlinear causality method. The contributions of this study can be evaluated through the aspects of energy, the environment, and econometric contributions. In fact, the NBARDL method benefits from three different approaches: the autoregressive distributed lag model (ARDL) of [18]; a well-known method used to investigate cointegrated long-run relationships that is generalized to the bootstrapping ARDL method; and the BARDL method, proposed by [19] to overcome degenerate cases in cointegrated relations in the ARDL of [18]. However, both the ARDL and BARDL methods allow for the examination of strictly linear relations. Recently, the ARDL method was generalized to NARDL, a nonlinear ARDL [20], as a method to allow for the examination of asymmetric and nonlinear relations in the long run, short run, and/or both. In contrast, NBARDL and the Granger causality modeling extension of NBARDL are novel methods that integrate bootstrapping and nonlinearity simultaneously into cointegration and causality relations. The method is advocated by [6] as a hybridization of bootstrapping BARDL and nonlinear NARDL methods and achieve robust results for nonlinearity and degenerate cases simultaneously in an ARDL-type cointegration and nonlinear causality. In this study, the NBARDL and NBARDL models in vector form are utilized to examine the asymmetric effects of the FP and MP by distinguishing between expansionary and contractionary characteristics in addition to examining the effects of renewable energy and total energy and technology on environmental pollution. Furthermore, the paper is a seminal paper in this respect and, as seen in the Literature Review Section, there are few papers that study the asymmetric effects of FP and MP instruments on the environment by using NARDL, and no paper utilizes the NBARDL and its nonlinear Granger causality extension to investigate the asymmetric effects of the MP and FP in addition to examining the effects of technology, energy, and renewable energy simultaneously on environmental degradation. This study is unique in that two types of causality analyses are used to obtain comparative and robust results, i.e., traditional causality methods based on linear causal analyses in addition to a novel nonlinear causality

method by [6]. The inclusion of the new method and the comparison of the results to the traditional linear method is crucial to derive adequate policy recommendations.

If an overlook is presented, two different methods are utilized for the causality analysis. The first one is the bootstrapping BARDL Granger causality (BARDL-GC) method. The method assumes the error-correction mechanism (ECM) to be determined from a BARDL method and utilizes bootstrapping to overcome degenerate cases of cointegration. The second method, NBARDL Granger causality (NBARDL-GC), allows for nonlinearity and asymmetry by including expansionary and contractionary policies in the model specification. With the use of NBARDL in the error correction specification, the second method benefits from bootstrapping and nonlinearity in the ARDL specification to define the error correction in the long-run mechanism. Therefore, both methods benefit from bootstrapping for achieving robustness against degenerate cointegration cases and the novel NBARDL-GC method further includes the asymmetric policy effects to be included in the long-run equation and the ECM of the error-correction vector in Granger causality testing.

Accordingly, by obtaining the causal effects from two different methods, we provide a comparative analysis. If the direction of the causality is determined from one variable to another, a novel NBARDL-GC is used in the study. Furthermore, the BARDL-GC method provides confirmatory basis for the analysis. Therefore, the two methods are used in conjunction. Typically, the direction of causality is considered as being accurate if the direction of the causalities is simultaneously determined using both methods. However, though the first method provides robust information against bootstrapping, the novel NBARDL-GC method is expected to provide a complete picture by differentiating between the expansionary and contractionary policy types. Furthermore, if the Granger casualty from one variable to another is accepted with the NBARDL-GC method, either for the expansionary or contractionary policy, one can accept this as evidence of causality and a confirmation of the results derived from the BARDL-GC method. However, researchers should be cautious since the effect can be different under the expansionary and contractionary policies, and even the direction of causality can be altered under different policies. Therefore, after the acceptance of causality from a policy variable to the environmental emissions or energy variables, two methods should be used simultaneously. Nonetheless, the specific causal effect can be specific to a certain type of economic policy, expansionary or contractionary, while the linear method fails to capture the specific causality. Hence, the new method provides insightful information for this matter. Lastly, in addition to the causality analysis, the coefficient estimates obtained from the NBARDL model are utilized to discuss the effects of the explanatory variables analyzed.

Therefore, this paper contributes in three different ways. First, to our knowledge, it is the first study that analyzes the cointegration and Granger causality between energy and technology policies, REN, and fossil fuel energy consumption and energy efficiency, in addition to the MP and FP policies and environmental pollution. Second, the paper utilizes the novel NBARDL method and its Granger causality extension, the NBARDL-GC analysis to obtain new insights regarding the energy environment nexus, and the MP and FP policies and environment nexus. With the use of the selected methods and variables, the paper provides a bridge between the two strands of literature, one focusing on the environment-MP and/or FP nexus, the other focusing on energy and/or renewable energy-environment nexus. Further, the paper introduces energy efficiency as an additional energy policy variable to the relationship. Lastly, the period we analyze covers both Industry 3 and Industry 4 revolutions (I3&4). I3&4 is intricately connected to the evolution of ICT (information and communication technology) [21]. As industrial processes evolve to become more intelligent, this transformation is facilitated by the integration of technologies, such as IoT and IoS, i.e., the Internet of Things and Internet of Services [6]. These interlinked networks empower the sectors to launch a continuous supply chain and enable smart manufacturing operations [6]. The adoption of industrial and technological policies aimed at fostering technological progress can exert considerable influence on energy usage and, consequently, the environment. Therefore, it is crucial to incorporate considerations of

energy and technology policies and the economic policies of the MP and FP into our analysis. This research also adds value by examining the interrelationships and causal links among variables, such as renewable and fossil fuel energy consumption levels, energy efficiency, technology policy, MP (monetary policy), FP (fiscal policy), and environmental pollution, measured through CO_2 emissions.

A literature review is presented in Section 2. Section 3 presents the econometric methodology. Section 4 includes the empirical findings. The discussion and conclusion are presented in Section 5.

2. Literature Review

The investigation of the effects of economic policies in the contexts of the FP and MP on different types of energies and environments has been conducted in a selected set of empirical literature. Among these, various papers employ methods that allow for nonlinearity and asymmetry with comparisons to linear approaches. Sohail et al. analyzed the effects of uncertainty in the MP on REN in the USA by applying both the symmetric and asymmetric ARDL estimation methods [22]. Based on their analysis, the linear approach revealed that monetary policy uncertainty had adverse impacts on REN in both the short and long runs. However, MP uncertainty did not result in any significant alterations in NREN in the short and long runs [23]. Their findings also showed that positive shifts in MP uncertainty resulted in unfavorable effects, while a negative shift in MP uncertainty had positive effects on REN in the short run. Consequently, with regard to REN in the short run, the influence of positive shifts in MP uncertainty was not statistically significant; negative shifts in MP uncertainty had a positive influence, which was confirmed to be statistically significant [22]. In terms of the nonlinear model, REN increased after undesirable shocks to MP uncertainty, while NREN decreased after such shocks, signifying that the effects of the MP were nonlinear, and the study underlined the importance of distinguishing the types of economic policies and their asymmetric effects [22].

Bildirici et al. conducted an analysis using a nonlinear bootstrapping NBARDL model to inspect the influences of the FP, MP, energy use, and production on CO_2 levels in Türkiye in 1978–2021. By generalizing the NBARDL to NBVARDL in vector form, they proposed bootstrapping to improve the results obtained by ARDL and NARDL methods in nonlinear causality testing [6]. Their empirical findings showed that both expansionary FP and MP resulted in inclines in the emissions of CO_2, and by applying the nonlinear method over the linear counterpart, the study revealed that the contractionary FP also had positive effects on emissions in specific regimes, in contrast to the general tendency in the literature discussing the negative impacts of expansionary economic policies on the degradation of the environment [6].

Another work on the effects of the MP by Razmi et al. [16] examined the effects of monetary policy instruments, specifically the interest rate and money supply, on the renewable energy generation (REG) in Iran, by focusing on the generation aspect, instead of the consumption of energy, between 1984 and 2016, using the Kalman filter and vector autoregressive (VAR) methods. By utilizing the total REG and by distinguishing between selected types of bioenergy (biomass and biogas) generations, as well as the total values of solar, wind, and hydropower generations, the Kalman filter results showed that both MP coefficients were unstable during the war years, the money supply coefficient was relatively stable in the peace years, and the interest rate coefficient was not stable for all types of REGs, which were shown to be sensitive to crises [16]. Razmi et al. also showed that an increase in real interest rates to achieve contractionary MPs negatively affected both the total REG and total hydropower, solar, and wind energy generations; conversely, an increase in real interest rates affected the bioenergy generation positively [16]. For their results obtained with the VAR model, only the money supply variable was shown to influence the REG.

Qingquan et al. analyzed the effects of the MP on CO_2 for a sample in 1990–2014 in Asian economies [8]. In their research, they incorporated income, remittances, fossil fuel usage, urbanization, and human capital variables. Their findings, derived from co-

integration tests conducted by Pedroni and Kao, as well as data analyses using DOLS and FMOLS estimators, revealed that, if the MP was expansionary, it increased CO_2 emissions, whereas the contractionary MP had the opposite effect. Furthermore, their results indicate the importance of the control variables and that human capital improvement reduces CO_2, remittances, and fossil fuel consumption levels, leading to inclines in CO_2 [8].

Furthermore, the association of public expenditures and energy-related issues were investigated by relating government spending to CO_2 emissions [23–25], environmental quality [26–28], and energy intensity [29]. Chien et al. conducted an analysis of the impact of green FPs on energy efficiency between 2010 and 2020. They found that the substantial and continuous implementation of these policies proved highly effective in enhancing energy efficiency levels, consequently reducing energy poverty [30]. Furthermore, there are studies that investigate the consequences of applied green tax based on the amount of environmental pollutants, such as CO_2 and SO_2, municipal waste, wastewater discharge, and deforestation [31]. Moreover, some studies emphasize that the environmental taxes negatively affect polluting emissions [32–39]. Some studies point out the limited effects of the environmental taxes intending to reduce environmental damage [40–43].

The efficacy of environmental policy strictness was analyzed and its effectiveness was explored in the literature in the context of environmental regulations measured by variables, including a stringency of environmental regulations in addition to the environmental regulation of applications [37,44–51]. Wolde-Rufael and Mulat-Weldemeskel provided a combined analysis of environmental policy stringency and environmental taxes [52]. By analyzing seven economies with data gathered between 1994 and 2015, they concluded that the strictness of policies towards the environment did not reduce CO_2 emissions in the early stages; however, later, it became effective in reducing such emissions [52] in addition to stressing a negative connection between CO_2 emission levels and the number of green taxes. While they proposed that implementing strict environmental protocols and raising environmental taxes could have a substantial effect on lowering emissions, the nations being studied need to be aware of the challenge of simultaneously preserving the environment and fostering economic growth [52].

By combining the effects of FP and MP economic policies, Chishti et al. analyzed the BRICS economies in 1985–2014 [13]. Using ARDL estimations, they concluded that, while an expansionary FP increases the greenhouse effects of CO_2, the contractionary FP is effective in decreasing the effects of CO_2 [13]. In terms of the MP, their findings show that as the expansionary MP worsens, the contractionary MP enhances environmental quality [13]. Another study that focuses on G7 countries is [17], and in their results for a sample in 2000–2018, they show that the expansionary FP increases investments in renewable energy generation, while the expansionary MP has the opposite effect: it reduces investments in renewable energies. Muhafidin [53] analyzed the Indonesian economy with samples from 1973 and 2018 with ARDL models. The findings indicate that both the increases in the exchange and interest rates result in environmental degradation [53]. By applying the NARDL model for the data of Pakistan between 1985 and 2019, Ullah et al. examined how the FP and MP have asymmetric impacts on environmental pollution. Their answers showed that short FP shocks, negative or positive, created surges in CO_2 emissions; however, such FP shocks resulted in a reduction in CO_2 emissions in the long run [54].

Bhowmik et al. explored the implications of uncertainty in the trade policy, FP, and MP on emissions in the USA in the context of an environmental version of the infamous Phillips curve with ARDL models [55], and their empirical findings suggested that MP uncertainty increased CO_2 emissions, while FP uncertainty reduced them [55]. Interestingly, their long-run findings suggested that uncertainty in an economic policy affected emissions and, in the short run, such effects disappear [55]. Mahmood et al. also conducted an analysis of the immediate and extended consequences of the MP and FP on CO_2 emissions by distinguishing between consumption- and territory-based emissions in GCC countries [56]. Their results reveal that both policies have strong implications on the environment, and although the MP is effective in the long run only, the FP is shown to be effective both in

the long- and short runs [56]. Li et al. investigated the impacts of the FP, REN, and NREN, and the strictness of environmental policies on trade-adjusted CO_2 emissions in BRICS economies. They utilized AMG and CCEMG estimators, along with panel causality tests, to analyze a sample in 1990–2019 [57]. Their empirical findings stress that the expansionary FP in the context of government expenditures and NREN increases CO_2. In contrast to a stringent environment policy, the contractionary FP measured with taxation and REN reduces CO_2. Moreover, the results show the causal effects of expansionary FP and contractionary FP policies and REN on CO_2 levels [57].

3. Method

The methods for bootstrapping in ARDL Long-run relationships in time series variables can be analyzed using the autoregressive distributed lag (ARDL) model of Pesaran et al. (henceforth, PSS) [18]. This model is designed to work with time series data that have varying or uncertain orders of integration. What sets it apart from earlier cointegration approaches is its use of bound testing, which involves both *F*-tests and *t*-tests to ascertain the presence of cointegration. However, the method is not prune to certain conditions, (i) applicability to small samples and a correction for revised critical values in this setting [6]; (ii) necessity of the existence of single cointegration vector [6], otherwise, the PSS method provides inconsistencies; (iii) PSS's ARDL method not being robust to degeneration in cointegration relationships, which could be controlled by bootstrapping [6,58]; (iv) nonlinearity in relationships is avoided in the linear traditional ARDL model [20]. The integration of nonlinear ARDL and bootstrapping ARDL methods and the novel NBARDL method provide an important solution to the critiques above [6]. Further, the bootstrapping ARDL (BARDL) aims at developing a set of critical values achieved with Monte-Carlo and bootstrapping by [59] to control the degenerate cases of cointegration. The recent NBARDL method proposed by [6] integrated both approaches: bootstrapping in line with the BARDL model from [58] and nonlinearity in the form of the NARDL model from [20]. Furthermore, the novel NBARDL was generalized to nonlinear bootstrapping Granger causality testing by [6].

Long-run relationships may involve two kinds of degenerations: the so-called first-type degeneration occurs when the dependent variable is not involved in long-run relationships, while the second type occurs if the independent variables disappear in the long-run relationship [19,58] in the ARDL model of Pesaran et al. (PSS) [18]. The model generated by PSS could not eliminate the first type [60]. The bootstrap ARDL test introduced by [19,58] was able to solve this problem by generating a set of F- and *t*-test critical values [19].

3.1. Generalization of the ARDL Model to a Nonlinear Bootstrapping NBARDL Model

The linear ARDL model of PSS delivers the basis for the asymmetric NARDL model, a generalization of the ARDL model of PSS to a special type of asymmetric nonlinearity. The PSS's ARDL model is given as:

$$y_t = c + \delta y_{t-1} + \beta x_{t-1} + \sum_{i=1}^{n} \beta_i \Delta x_{t-i} + \sum_{i=0}^{m} \gamma_i \Delta y_{t-i} + \epsilon_t \tag{1}$$

where Δ denotes first differencing, such as $\Delta y_t = y_t - y_{t-1}$, due to a set of unit root and stationarity tests suggesting that the series follow an I(1) process, i.e., with an integration order equal to 1. To test the cointegration, PSS proposed the F_{PSS} test with:

$$H_0 : \ \delta = \beta = 0 \tag{2}$$

In the long run, the model becomes:

$$y_t = \beta^+ y^+ + \beta^- y^- + v_t \tag{3}$$

where β^+ *and* β^- are long-run parameters, x_t is an I(1) scalar variable. y_t is defined as:

$$y_t = y_0 + y_t^+ + y_t^- \tag{4}$$

where y_0 is the initial value, then:

$$y_t^+ = \sum_{j=1}^{t} \Delta y_j^+ = \sum_{j=1}^{t} \max(\Delta y_j, 0) \tag{5}$$

$$y_t^- = \sum_{j=1}^{t} \Delta y_j^- = \sum_{j=1}^{t} \min(\Delta x_j, 0) \tag{6}$$

By incorporating Equations (5) and (6) to the the ARDL model given in Equation (1), one can obtain the nonlinear NARDL presentation below:

$$\Delta x_i = c + \sum_{i=1}^{m} \beta_i \Delta x_{t-i} + \sum_{i=0}^{n} \left(\varphi_i^+ \Delta y_{t-i}^+ + \varphi_i^- \Delta y_{t-i}^- \right) + \delta x_{t-1} + \vartheta^+ y_{t-1}^+ + \vartheta^- y_{t-1}^- + \varepsilon_t \tag{7}$$

where Δ denotes that variables are first differenced and ε_t is a normally distributed, white noise i.i.d. process. The parameters are asymmetric in the long-run equation and are given as $\beta^+ = -\vartheta^+/\delta$, $\beta^- = -\vartheta^-/\delta$, where:

$$\delta = \sum_{i=1}^{m} \varnothing_{i-1}, \ \beta_i = -\sum_{j=i+1}^{m} \varnothing_j \text{ for } i = 1, \ldots, m-1 \tag{8}$$

$$\vartheta^+ = \sum_{i=0}^{n} \vartheta_i^+, \ \vartheta^- = \sum_{i=0}^{n} \vartheta_i^-, \ \varphi_0^+ = \vartheta_0^+, \ \varphi_i^+ = -\sum_{j=i+1}^{n} \vartheta_i^+ \text{ for } i = 1, \ldots, n-1 \tag{9}$$

$$\varphi_0^- = \vartheta_0^-, \ \varphi_i^- = -\sum_{j=i+1}^{n} \vartheta_i^- \text{ for } i = 1, \ldots, n-1. \tag{10}$$

No cointegration null and alternative hypotheses can be formulated using the parameters in Equation (4) as:

$$H_0: \ \delta = \vartheta^+ = \vartheta^- = 0 \tag{11}$$

$$H_1: \ \delta \neq \vartheta^+ \neq \vartheta^- \neq 0. \tag{12}$$

To address a potential of non-zero contemporaneous correlations among residuals and explanatory variables, Shin et al. [20] proposed the following representation of a nonlinear conditional ECM model:

$$\Delta y_t = c + \rho \, ECM_{t-1} + \sum_{j=1}^{m} \gamma_j \Delta x_{t-j} + \sum_{j=0}^{n} (\pi_j^+ y_{t-j}^+ + \pi_{t-j}^- y_{t-j}^-) + \epsilon_t \tag{13}$$

where

$$\pi_0^+ = \vartheta_0^+ + \mu, \ \pi_0^- = \vartheta_0^- + \mu, \ \pi_j^+ = \varphi_j^+ - \pi' \Lambda_j \text{ and } \pi_j^- = \varphi_j^- - \pi' \Lambda_j \text{ for } j = 1, \ldots, n. \tag{14}$$

The null hypothesis for symmetric long-run and short-run relationships are given as:

$$\beta^+ = \beta^-, \text{ and, } -\vartheta^+/\delta = -\vartheta^-/\delta \tag{15}$$

The short-run asymmetry condition is $\vartheta^+ = \vartheta^- = \vartheta$; based on the NARDL model of [20], the model becomes:

$$\Delta y_t = \rho \, y_{t-1} + \boldsymbol{\vartheta x_{t-1}} + \sum_{j=1}^{m} \gamma_j \Delta x_{t-j} + \sum_{j=0}^{n} (\pi_j^+ y_{t-j}^+ + \pi_j^- y_{t-j}^-) + \epsilon_t \tag{16}$$

where the long-run asymmetry condition is given by either $\pi_i^+ = \pi_i^-$ or $\sum_{j=0}^n \pi_j^+ = \sum_{j=0}^n \pi_j^-$ so that the model becomes:

$$\Delta y_t = \rho\, y_{t-1} + \boldsymbol{\vartheta}^+ \boldsymbol{x}_{t-1}^+ + \boldsymbol{\vartheta}^- \boldsymbol{x}_{t-1}^- + \sum_{j=1}^m \gamma_j \Delta y_{t-j} + \sum_{j=0}^n \boldsymbol{\pi_i} \boldsymbol{\Delta x_{t-i}} + \epsilon_t \tag{17}$$

3.2. Nonlinear Bootstrapping NBARDL Granger Causality (NBARDL-GC) Model

The NBARDL model in the previous section allowed for controlling degenerate cases of cointegration with bootstrapping and integrated asymmetric policy effects with the nonlinearity approach as a hybridization of two approaches: BARDL and NARDL. The newly developed NBARDL model was extended to Granger causality modeling. The novel NBARDL Granger causality (NBARDL-GC) model following [6] was utilized as follows. Assume a vector-ECM model, which utilizes a cointegration vector derived from the NBARDL model given in the previous section to be written in a reduced form with 2 vectors and 2 variables and a single ECM in each vector is presented as:

$$\Delta x = A_{10} + \sum_{i=1}^m B_{1i} \Delta x_{t-i} + \sum_{i=0}^m \left(\varphi_i^+ \Delta y_{t-i}^+ + \varphi_i^- \Delta y_{t-i}^- \right) + \xi_1\, ECM_{t-1} + \varepsilon_{1t} \tag{18}$$

$$\Delta y_t = A_{20} + \sum_{j=1}^m \lambda \Delta y_{t-i} + \sum_{i=0}^n \left(\beta_i^+ \Delta x_{t-i}^+ + \beta_i^- \Delta x_{t-i}^- \right) + \xi_2\, ECM_{t-1} + \varepsilon_{2t} \tag{19}$$

where ECM_{t-1} is obtained from the residuals of the NBARDL model, and ε_{it} is normally distributed as previously defined. In the model, two parameters, ζ_1 and ζ_2, measure the speed of convergence towards the long-run equilibrium following 1 standard deviation shock within one period. For an error correction to occur, necessary conditions require negative estimates for both parameters being statistically significant and negative, in addition to being estimated between 0 and -1. For Equations (18) and (19), nonlinear asymmetric Granger causalities can be tested with the following null hypotheses $H_0 : \varphi_i^+ = \varphi_i^- = 0$ and $H_0 : \beta_i^+ = \beta_i^- = 0$.

3.3. Research Questions

The research questions are divided into two fields. The first field focused on the effects of the FP and MP, technology policy, and energy policy on the environment. Do the MP, FP, technology and energy policies, and shifts in the MP and FP and energy policies and technology policies have environmental impacts? Are the impacts of MPs and FPs under expansionary and contractionary policies on environmental degradation distinguished; in other words, what are the asymmetric influences of MPs and FPs on CO_2 emissions? Following the findings regarding the above-mentioned policies and factors, which policy proposals can be advised for policy makers?

In the second field, the study aimed at examining energy policies in terms of three energy variables. Among these, REN and NREN energy variables are commonly applied in the literature. However, energy efficiency is an unexplored feature of energy and technology policies. In this context, what are the impacts of energy policies on the environment and, if compared, what are their comparative effects on altering the levels of CO_2 emissions? In addition to these aims presented in the research questions, a last-but-not-least dimension of the paper focuses on the econometric methodology used in the study by utilizing the novel NBARDL and NBARDL Granger causality methods, which benefit from both bootstrapping ARDL and nonlinear NARDL models and their extension to Granger causality modeling.

3.4. Proposed Model in This Study

In this study, we examine if renewable energy, fossil fuel energy, and energy policies measured with energy efficiency; economic growth and technology policies measured with technology patents; and economic policies of FPs and MPs distinguished for their asymmet-

ric impacts had significant effects on the environmental degradation measured with CO_2 emissions. As mentioned in Section 2, there are studies analyzing the environmental effects of FPs and MPs simultaneously. In this study, energy policies are that energy efficiency is a newly introduced measure of energy policies in addition to the inclusion of technology policies in our models. In terms of the econometric assessment, the proposed method is novel in avoiding the degenerate cointegration cases with bootstrapping and by including the asymmetric effects of economic policies in a nonlinear setting both in short and long-run equations.

Pesaran et al. introduced two tests, *F*- and *t*-tests to validate the findings [18]. Both tests employed non-standard distributions and incorporated new critical values for the testing procedure. The model used in this research was initially presented with a linear ARDL configuration as follows:

$$
\begin{aligned}
\Delta CO_t = c + \sum_{i=1}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \Delta Y_{t-i} + \sum_{i=0}^{k} \varphi_i \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i \Delta\, DC_{t-i} + \\
\sum_{i=0}^{z} \delta_i \Delta G_{t-i} + \sum_{i=0}^{q} A_i \Delta REN_{t-i} + \sum_{i=0}^{r} K_i \Delta EF_i + \sum_{i=0}^{h} Z_i \Delta PT_{t-i} \\
w_0 CO_t + w_1\, Y_{t-1} + w_2\, EC_{t-1} + w_3\, DC_{t-1} + w_4\, G_{t-1} + w_5 REN_{t-1} \\
+ w_6\, EF_{t-1} + w_7\, PT_{t-1} + \varepsilon_t
\end{aligned}
\tag{20}
$$

where the variables' annotations are given as economic growth (*Y*), energy consumption (*EC*), renewable energy consumption (*REN*), fossil fuel energy consumption (*EC*), energy efficiency (*EF*), technology patents (*PT*), and, lastly, CO_2 emissions (*COs*). The short-run impacts are included with the "first-differenced" variables, and long-run impacts are presented in levels with long-run parameter estimates of $w_1, \ldots, w_6$, which are normalized at w_0.

Following the modeling idea of Shin et al. [20], variables ΔDC_t and ΔG_t are decomposed into two time-series variables, denoted by plus and minus superscripts to indicate inclines and declines, respective to MPs and FPs. As mentioned above, we did not decompose ΔPT_t and ΔEF_t.

The decompositions can be shown by the partial sum approach:

$$
DC_t^+ = \sum_{j=1}^{t} \Delta DC_j^+ = \sum_{j=1}^{t} \max\left(\Delta DC_j, 0\right)
\tag{21}
$$

$$
DC_t^- = \sum_{j=1}^{t} \Delta DC_j^- = \sum_{j=1}^{t} \min\left(\Delta DC_j, 0\right)
\tag{22}
$$

$$
G_t^+ = \sum_{j=1}^{t} \Delta G_j^+ = \sum_{j=1}^{t} \max\left(\Delta G_j, 0\right)
\tag{23}
$$

$$
G_t^- = \sum_{j=1}^{t} \Delta G_j^- = \sum_{j=1}^{t} \min\left(\Delta G_j, 0\right)
\tag{24}
$$

where DC_t^+ and G_t^+ variables are calculated as the sum of positive innovations in the domestic credits and government expenditures, respectively, referring to expansionary MPs and FPs. The terms DC_t^- and G_t^- are given by the sum of negative innovations in the domestic credits and government expenditures, respectively, representing contractionary MPs and FPs. Accordingly, the extended error-correction model is presented as:

$$
\begin{aligned}
\Delta CO_t = c + \sum_{i=1}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \Delta EC_{t-i} + \\
\sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ + \sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ \\
+ \sum_{i=0}^{q} A_i \Delta REN_{t-i} + \sum_{i=0}^{r} K_i \Delta EF_i + \sum_{i=0}^{h} Z_i \Delta PT_{t-i} \\
+ w_0\, CO_{t-1} + w_1\, Y_{t-1} + w_2\, EC_{t-1} + w_3 DC_t^+ + w_4 DC_t^- \\
+ w_5\, G_t^- + w_6\, G_t^+ + w_7\, REN_{t-1} + w_8\, EF_{t-1} + w_9\, PT_{t-1} + \varepsilon_t
\end{aligned}
\tag{25}
$$

In a reduced form, by replacing the part denoting the long-run relation with ECM_{t-1}, the error-correction model reduces to the following equation:

$$
\begin{aligned}
\Delta CO_t = {} & c + \sum_{i=1}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} \\
& + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ + \sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ \\
& + \sum_{i=0}^{q} A_i \, \Delta REN_{t-i} + \sum_{i=0}^{r} K_i \, \Delta EF_i + \sum_{i=0}^{h} Z_i \, \Delta PT_{t-i} + \zeta_1 \, ECM_{t-1} + \varepsilon_t
\end{aligned} \tag{26}
$$

where ζ_1 indicates the speed of the adjustment parameter measuring the percentage of the convergence to the long-run equilibrium within one period. The usual conditions for the mechanism to hold are i. having a statistically significant ζ_1 error-correction parameter; ii. being estimated with a negative sign so that $\zeta_1 < 0$; and iii. being in the range of $0 < \zeta_j < 1$, i.e., between 0 to -1. Then, since the sample is yearly, the number of years needed for the convergence towards the long-run equilibrium to occur is given by $1/\zeta_1$.

For Granger causality testing purposes and given that we have 8 variables, and once the FPs and MPs are distinguished for their positive and negative realizations, i.e., expansionary and contractionary MPs and FPs, a vector autoregressive model (VAR) consists of 10 vectors. Among these vectors, Equation (26) is the 1st vector, where the Granger non-causality $H_0 : \gamma_i = 0$ null hypothesis tests the non-causality from Y to CO. Therefore, Granger non-causalities were tested with the remaining 9 separate null hypotheses. Among these, five assumed linear causal links so that the parameters γ_i, φ_i, A_i, K_i, Z_i should be set to be equal to zero against the alternatives of the Granger causality from the relevant variables to the CO$_2$ emissions.

Furthermore, the causal effects from expansionary and contractionary MPs and FPs were tested by allowing for asymmetry in the causality. For instance, two separate null hypotheses, $H_0 : \lambda_i^+ = 0$ and $H_0 : \lambda_i^- = 0$, allowed for testing the non-causality from an expansionary MP to CO and from a contractionary MP to CO separately. Hence, expansionary and contractionary FPs were tested by forming tests that assumed δ_i^- and δ_i^+ equal to zero in two different null hypotheses of Granger non-causalities. To save space, this section provided the Granger causality test method for the first vector of the VAR model, and the procedure necessitates the examination of causalities in all the vectors of the VAR. To save space, the remaining vectors of the VAR model following the first vector given in Equation (26) are presented in Appendix A.

3.5. Flowchart of the Methodology and Empirical Analyses

The paper employed the NBARDL- and NBARDL-based Granger causality analyses discussed in the Methods Section. Both methods benefitted from bootstrapping to avoid degenerate cases of cointegration. To present an outlook of the methodology we followed, a flowchart is presented in Figure 1. The steps presented include tests and the estimation strategies followed in the econometric method. As shown in the research model presented above, the method includes the asymmetric impacts of MPs and FPs, and after the comparative analysis of the causality tests, policy recommendations are presented in the last section.

In Figure 1 below, similar to the NBARDL Granger causality, a bootstrapping BARDL specification is included to the traditional Granger causality method.
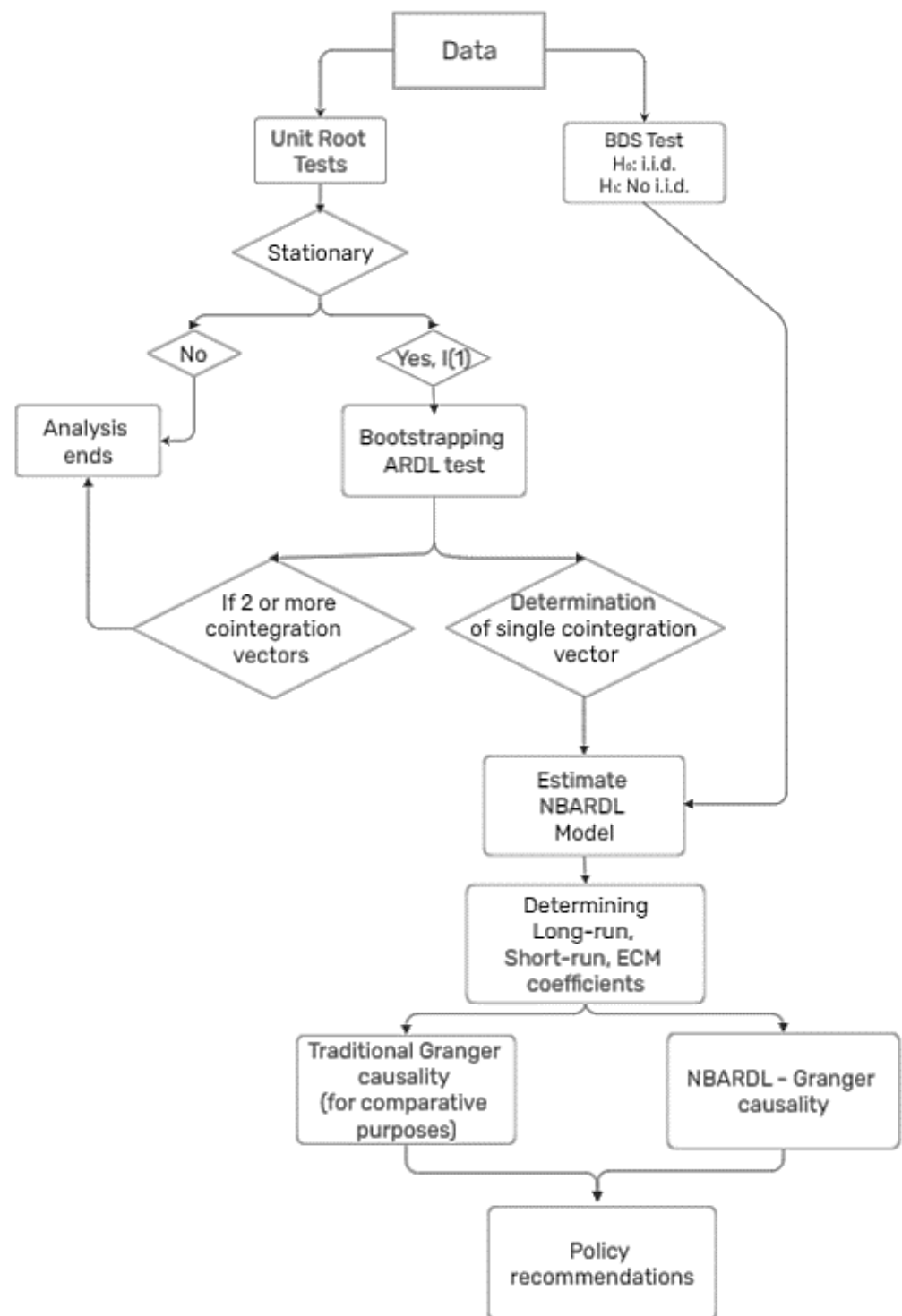
Figure 1. Flowchart depicting the modeling steps and methods.

4. Data and Empirical Results

4.1. Data

The data utilized in this analysis of the USA were yearly obtained and covered the periods of 1972 and 2022. Carbon dioxide emissions were used to measure environmental pollution levels. Energy consumption, government expenditure, domestic credits, and real GDP were obtained from World Bank. Technology policies were measured by technology patents. However, the transition from the industrial community to services and from there to I3&4 could not be measured by this variable. As appropriate proxies for I3 & 4,

Internet and communication technologies and artificial intelligence (AI) patents could be used following [61,62]. However, these variables, especially the AI patent variable, was not available until recently, as expected. Similarly, ICT patents could not be obtained until 1972. Hence, we used a more general patent variable: technology patents. As mentioned above, the energy policy variable was used as the energy efficiency value. This variable was used as a policy recommendation in some studies in recent years. However, we used this variable as an energy policy tool. Energy efficiency was proxied with the energy intensity, which was calculated by the US Energy Information Administration (EIA). Renewable energy and fossil fuel energy consumption levels were obtained from British Petrol.

Detailed explanations are presented in Table 1 with sources.

Table 1. Descriptive statistics.

Abbreviations:	EC	REN	Y	DC
Variable:	Fossil fuel energy consumption	Renewable energy consumption	Real GDP	Domestic credits
Sources:	British Petrol	British Petrol	World Bank	World Bank
Sd	0.126948	0.212603	0.176427	0.137782
Sk	−0.614128	0.884125	−0.242417	−0.013539
Kr	1.922306	1.960510	2.12599	2.659263
Jb	3.473831	3.997697	4.021	3.321408
Abbreviations:	G	CO	EF	PT
Variable:	Government expenditures	CO$_2$ emissions	Energy efficiency	Technology patents
Sources:	World Bank	World Bank	Energy info. Admin.	World Bank
Sd [1]	0.142088	0.156672	0.130258	0.304410
Sk	−0.714237	−0.398695	0.118911	−0.161753
Kr	1.982635	1.982912	1.971749	2.062350
JB	3.387979	3.549384	3.625209	3.49214

[1] Sd, Sk, and Kr are the standard deviation, skewness, and kurtosis statistics, respectively. JB is the Jarque–Bera normality test statistic, which follows a Chi-squared distribution with 2 degrees of freedom.

To reduce skewness, the data were subject to natural logarithms. In Table 1, the skewness values are negative, except for REN and EF. The kurtosis statistics are close to 2. The Jarque–Bera test statistics are lower than 5.99; the critical Chi-squared table value is at a 5% significance level for 2 degrees of freedom for all variables. The results specify that variables have a normal distribution and deviations of skewness and kurtosis from their expected values of 0 and 3; for normality, they are statistically low enough so that they can be neglected.

4.2. Unit Root Tests

As an initial step, the variables were evaluated for stationarity. The unit root test results are given in Table 2 where the findings determined by ADF and PP tests are reported. The variables in levels were non-stationary and once first-differenced; the test results indicate stationarity. Therefore, the variables are I(1). Hence, all were first differenced in the analyses that followed.

4.3. BDS Test Results

The BDS test of [63] was conducted to evaluate the i.i.d.ness of the data. The test is also known to be effective in determining nonlinearity. The test results are depicted in Table 3 at different dimensions of the BDS test, and the overall results indicate that series are nonlinear at conventional significance levels. This discovery further strengthened the rationale for utilizing the NBARDL model in the following section.

Table 2. ADF and PP unit root test results.

		Level		First Difference		Decision
Variable:	ADF	PP	ADF	PP	
Y	−1.6041	−1.8823	−6.2454 *** [1]	−6.2490 ***	I(1)
REN	0.0048	1.8329	−7.8344 ***	−2.664 **	I(1)
EC	−1.833	−1.07247	−3.9231 **	−6.4475 ***	I(1)
DC	0.8339	−1.8942	−5.6483 ***	−6.5634 ***	I(1)
G	−1.801	2.1451	−5.488 ***	−6.0791 ***	I(1)
CO	0.2987	1.1166	−8.0907 ***	−8.30801 ***	I(1)
EF	−0.9538	−0.9522	−5.4894 ***	−6.5904 ***	I(1)
PT	−1.4136	−1.7423	−2.9877 **	−2.9962 **	I(1)

[1] *** and ** denote the statistical significance of the parameters at 1% and 5% levels of significance, respectively.

Table 3. BDS test results.

	CO		*Y*		*EC*		*REN*	
d	BDS [1]	z	BDS	z	BDS	z	BDS	z
2	0.175733	24.37787	0.198335	32.13581	0.204774	25.69920	0.170929	11.86474
3	0.285403	24.66526	0.335796	33.88420	0.348124	27.23319	0.270827	11.64068
4	0.353986	25.44394	0.433162	36.34468	0.447686	29.14139	0.326981	11.60903
5	0.397544	27.15319	0.502229	40.03553	0.517073	31.99711	0.353462	11.83889
6	0.426669	29.92775	0.552142	45.19296	0.564918	35.91426	0.354572	12.10524
	EF		*G*		*DC*		*PT*	
d	BDS	z	BDS	z	BDS	z	BDS	z
2	0.193777	33.47536	0.174194	14.71204	0.179819	27.34522	0.199350	30.14553
3	0.328467	35.50087	0.272932	14.34513	0.298526	28.23379	0.334665	31.74668
4	0.422786	38.17197	0.331196	14.45470	0.379745	29.82216	0.423856	33.67439
5	0.490320	42.25429	0.398241	16.48585	0.442399	32.96095	0.482623	36.69084
6	0.543138	48.28315	0.448986	19.04963	0.486018	37.12738	0.521462	40.99748

[1] BDS and z are the BDS and z test statistics at dimension *d* for *d* = 2, 3, . . ., 6. For all tests, the *p*-value is 0.000; the rejection of the null hypothesis that the tested series are independent and identically distributed and in favor of the acceptance of nonlinearity.

4.4. Affirming the Presence of a Single Cointegration Vector

In the implementation phase of the method, the bootstrapping ARDL (BARDL) method was used to determine the presence of only one cointegration vector. Then, nonlinear causality analyses were performed to identify the policy recommendations. As the BARDL method removes the degenerate cases, it is preferred over the ARDL model for dependent variable determination and cointegration testing methods. As explained in the Method Section, all variables were considered to be the dependent variable separately in each row of Table 4, where the remaining sets of variables were assumed to be the independent variables. The method allowed for testing the cointegration and degenerate cases and the existence of, if possible, a single cointegration vector [19,58] in accordance with [64].

Table 4. BARDL test results.

Dep. Var. | Indep. Var.	F	F*	F Indep	F* Indep	t	T*	Decision
co | ec, g, dc, y, ren, pt, ef	8.582	7.11	5.48	4.55	−3.42	−3.21	Cointegration
ec | g, dc, y, co, ren, pt, ef	0.987	3.05	2.22	2.98	−2.59	−3.72	No Cointegration
g | dc, y, co, ec, ren, pt, ef	2.991	4.28	4.27	4.96	−4.77	−3.97	No Cointegration
dc | y, co, ren, pt, ef, ec, g	3.507	3.41	3.48	4.36	−5.46	−3.26	Degenerate-1
y | co, ren, pt, ef, ec, g, dc	4.26	3.69	2.28	5.72	−5.79	−4.03	Degenerate-1
ren | co, y, pt, ef, ec, g, dc	1.47	2.19	2.75	3.01	−1.82	−2.88	No Cointegration
ef | co, y, pt, ec, g, ren, dc	3.69	4.83	3.26	2.89	−3.14	−3.09	No Cointegration
pt | co, y, ec, g, dc, ren, ef	5.27	4.68	3.44	4.62	−5.81	−3.71	Degenerate-1

In Table 4, the bootstrapping ARDL test method of [19] requires the examination of 6 different test statistics, F, F*, F Indep, F* Indep, t and T, to distinguish between cointegration, no-cointegration, degenerate case 1 and degenerate case 2. The results indicated the existence of a single cointegration vector given in the first row of Table 4.

4.5. Model Estimation Results

The bootstrapping bound tests revealed a cointegrated and, therefore, long-run connection, which was present only if CO was the dependent variable. In Table 4, the presence of 1 cointegration vector can be accepted after the examination of the calculated F, F*, t, and t* statistics of the BARDL cointegration test obtained through bootstrapping. The results confirm a cointegration at a 1% level of significance in the first row only. Hence, the results indicate the presence of a single long run forcing an association between energy-related EF, EC, and REN; technology-related PT; and MPs and FPs and their asymmetric values, i.e., contractionary and expansionary counterparts, with the carbon dioxide emissions within the bootstrapping methodology. The selected NBARDL model and the estimation results are conveyed in Table 5.

Table 5. Econometric model estimations.

Variable	Coefficient	*t*-Statistic	Variable	Coefficient	*t*-Statistic
Long-Run Coefficients [1]			**Short-Run Coefficients**		
DC_t	0.441635 *	1.940073	ΔDC_t	0.186877	1.359548
$DC_t{}^-$	−0.062185 **	−2.112573	$\Delta DC_t{}^-$	−0.048056	−0.112921
$DC_t{}^+$	0.782236 **	2.357173	$\Delta DC_{t-1}{}^-$	0.241635 **	2.240073
G_t	0.207885 **	2.11165	$\Delta DC_t{}^+$	−0.388811	−1.336554
$G_t{}^-$	0.054717 **	2.081097	$\Delta DC_{t-1}{}^+$	−0.559336 *	−1.856734
$G_t{}^+$	0.256864 ***	2.924147	ΔPT_t	0.338713 *	1.817119
EF_t	−1.694999 ***	−3.969050	ΔY_t	−0.008172	−0.013394
PT_t	0.077236 *	1.748311	ΔY_{t-2}	−0.031472 ***	−4.807200
Y_t	−0.839242 ***	−4.050064	ΔREN_t	−0.042285 **	−2.080865
REN_t	−0.040725 ***	−8.088873	ΔEC_t	0.737400 **	2.108500
EC_t	0.52501	0.18901	ΔG_t	0.209263 ***	2.687427
			$\Delta G_t{}^-$	0.198503 *	1.923772
			$\Delta G_t{}^+$	1.239858 **	2.425285
			ΔEF_t	0.000263 **	2.222457
			ΔEF_{t-1}	−0.432793 ***	−5.846397
			ECM_{t-1}	−0.672793 **	−2.15036
R^2	0.6431	Adj. R^2	0.5187	W_{LR-G}	8.82
AIC	−4.6412	LL	129.13	W_{SR-G}	4.66
BIC	−3.9395	F	46.4880	W_{LR-DC}	9.56
LM	1.47	RESET	0.63	W_{SR-DC}	4.92

[1] *, **, *** denote that the parameter is statistically significant at 10%, 5% and 1% significance levels, respectively. AIC and BIC are the information criteria of Akaike and Schwarz, LM is a Lagrange multiplier test statistic for a single structural break, LL is the log-likelihood, F is the F statistic for the overall model, R^2 and Adj. R^2 are the usual R-square and adjusted R-square values for the overall goodness of fit. RESET denotes Ramsey's test statistic for correctly specified models. W_{LR-G} and W_{SR-G} are the asymmetry test statistics for the long- and short-run fiscal policy parameters, respectively. Similarly, W_{LR-DC} and W_{SR-DC} are their monetary policy counterparts for the long and short runs. DC− and DC+ signify contractionary and expansionary MPs. G− and G+ are contractionary and expansionary FP variables. Δ is the first difference operator.

The first part of Table 5 focuses on the results of the long-run associations. If an overlook is presented to energy-related variables, both renewable energy and energy efficiency are observed to help in reducing the CO_2 emissions. The studies investigating environmental degradation and the energy nexus place special emphasis on renewable energy. As expected, an increase in REN reduces the environmental pollution measured with CO_2 emissions. However, following our results, EF is an imperative tool and comparatively, with a relatively significantly more negative parameter estimate, EF is the variable that mitigates emissions with a relatively greater effect after a 1% increase. Though REN has

negative effects on emissions, from another perspective, we can observe that, unless renewable energy is not well coupled with energy efficiency, CO_2 emission mitigation is not likely to occur. The long-run results indicate that increases in EF is crucial for CO_2 mitigation and a 1% point increase in energy efficiency reduces CO_2 levels by a 1.695% point: more than a one-to-one effect. Given the relatively lower estimate of the REN, this result makes EF a powerful tool for reducing environmental pollution levels and it highlights the importance of innovation and technology policies regarding energy efficiency. Economic growth also has a negative effect on CO_2 levels for the sample and period analyzed with the model. A 1% increase in Y results in a 0.83% reduction in CO levels, and its parameter is statistically significant at the 1% significance level. Technology patents in the economy also have positive parameter estimates; however, they are significant at the 10% significance level only and, at this level, a 1% incline in PT leads to a 0.077% point increase in CO_2 emissions. As a final energy variable, EC is included in the model. In the long run, a 1% point increase in the consumption levels of fossil fuel energy has no effect on the CO_2 emissions, while its positive effects could not be rejected in the short run.

MPs and FPs were included in three different variables in the model. For both, linear and asymmetric effects were included. In terms of the MP, the linear effect was examined with the parameter of DC, the effects of contractionary and expansionary MP policies with DC− and DC+, respectively. The linear effect of the MP was statistically significant at the 10% significance level only; at this level, a 1% upsurge in the MP results in a 0.44% increase in CO_2 emissions, degrading the environment. For their asymmetric effects, both the parameters of DC+ and DC− were statistically significant at 5% and indicated a high level of asymmetry with different signs: 0.782 and −0.062; positive effects of expansionary and negative effects of contractionary MPs. In contrast to the linear effect that highlighted the positive effects only, the asymmetric results indicated the distinguished response of emissions to both types of policies.

For FPs, if the linear effects followed by expansionary and contractionary FPs were evaluated, the parameter estimates of G, G+, and G− were 0.207, 0.054, and 0.256, respectively, all statistically significant at 5% (the latter was at 1%) and all pointed to the positive effects of FPs. The parameter of G is estimated as 0.207, the expansionary FP has a parameter estimate of 0.256, while the contractionary FP parameter estimate is 0.054 only: in contrast to the expansionary MP, the expansionary FP has positive effects on the emissions.

The short-run estimation results are evaluated in the second section in Table 5. The comparison between the effects of EF and REN in the short run resulted in important findings and also some confirmations for the short run. In the short run, the effect of EF is positive at period t; however, given the size of the parameter estimate (0.0002) of ΔEF_t being too close to zero, the positive effect could be neglected in this case. However, the first lagged effect is negative and large for ΔEF_{t-1}, a 1% point increase in EF in the last year leading to a 0.4327% decline in CO_t levels in the current year in the short run, signifying the CO_2 mitigation effects of EF also in the short run. However, there are sharp and negative effects of EF increases on emissions levels that occurr with a one-year lag, suggesting a dynamic relation. A 1% point incline in EF in the short run leads to a 0.43% point reduction in CO_2 emissions in the following year. Furthermore, REN has a negative effect on emissions levels. A 1% rise in REN leads to a −0.04% decline in CO_2 emissions and the CO_2 mitigation effect of renewable energy could not be rejected in the short run. The effect of REN is similar in terms of the size of its parameter to that of the long-run parameter. Moreover, both EF and REN prove to be significant tools for achieving environmental sustainability and are effective in improving the air quality both in the long and short run. In terms of PT, a 1% point incline in the current year results in a 0.338% point incline in CO_2 emissions. However, similar to the long-run results, the positive effect of technology patents is significant at the 10% significance level only. As the final energy variable, the parameter of ΔEC_t is statistically significant at 5% in the short run, indicating the positive effects of fossil fuel energy consumption on CO_2 emissions.

The total effects of FPs and MPs are again positive in the short run. However, this time, the effect of the FP is greater than that of the MP. While a 1% point increase in the FP results in a 0.21% upsurge, a 1% increase in the MP leads to an almost similar and positive response, a 0.19% upsurge in the CO_2 emissions. In the short run, the contractionary MP negatively affects CO_2 levels, reducing the emissions. However, for the first differenced variable of the MP, the coefficient estimate is positive; and the positive effect on the emissions could not be rejected. The expansionary MP together with its first lag, different from the long-run effect, results in a reduction in the CO_2 emissions levels. Both the expansionary FP and contractionary FP increases the emissions, while the effect of the expansionary FP is greater than that of the contractionary FP. Among the energy variables, the parameter estimate of ΔREN_t is -0.042; a 1% point incline in REN reduces emissions by 0.042% in the short run.

The model is recognized as being statistically significant at conventional levels of significance since the estimated F statistic exceeds the critical F value for the overall model, the RESET test denoting no model misspecification, and the LM test confirming no structural breaks in the remainder. As stated in the methodology, Wald tests were used to determine and test whether asymmetry was present. According to the results, both MPs and FPs that are expansionary and contractionary have an impact on environmental degradation in the long run. $W_{LR-G} = 8.82$ and $W_{SR-G} = 4.66$ for the long-run symmetry tests suggested a rejection of symmetry in the FP effects. Such findings also hold for the short-run symmetry tests suggesting a rejection of symmetry in favor of the asymmetry of MPs. The asymmetry test tests the equality of expansionary and contractionary FP parameters via an F test under the null hypothesis. Both long- and short-run symmetry tests confirmed the asymmetric effects of expansionary and contractionary FPs, given that WLR-G and WSR-G were higher than critical F at 5%. The long- and short-run test results confirm the asymmetry of effects for both FPs and MPs on CO_2.

4.6. Causality Results

In the study, two different causality tests are employed, and the causality results are presented in Tables 6 and 7. In the first one, we report the results obtained by assuming policy symmetry in Table 6 based on the Granger causality test, and this approach assumes the ECM obtained from the BARDL method, which is called BARDL-GC. In Table 7, we differentiate between the asymmetric effects of FPs and MPs, and we report the NBARDL-based Granger causality (NBARDL-GC) test results by incorporating the nonlinear and asymmetric effects of economic policies. In addition, both methods assume the controlling of the degenerate cases of cointegration by utilizing the ECM vector in the model derived from the bootstrapping methodology of [6,19].

The BARDL-GC causality results assume no asymmetric effects from the MP and FP variables (DC and G, respectively), without distinguishing between the contractionary and expansionary effects. In terms of the unidirectional causal links of the MP, unidirectional causalities were obtained from DC to CO, from DC to EC, from DC to EF, and from DC to REN, i.e., from the MP to all energy-related variables. The unidirectional effects of the MP also could not be rejected from DC to G, i.e., to FPs, and from DC to Y, i.e., to economic growth. Furthermore, the MP is the Granger-cause of CO, i.e., CO_2 emissions. Energy efficiency, EF, is not only the Granger-cause of CO, but also the Granger-cause of G, PT, and REN. Given the causal effects from DC to energy variables and the economic growth, MP appeared to be an important tool for not only affecting the economy, but also the renewable and fossil fuel energy policies and the FP. However, DC is not the Granger-cause of PT, and in fact, it is the other way around. Hence, technology patents presented causal effects on monetary policies and this is the same for G: PT Granger causes G, in other words the FP.

If the links from FP to the other variables are evaluated, we note that FP is the Granger-cause of CO_2 emissions, the FP is not the Granger-cause of energy consumption (EC); and the direction was the opposite for MP, the causal link was from MP to EC. In fact, EC is the Granger-cause of G, suggesting causal effects of EC on FP policies in the USA. Furthermore, PT and Y are the Granger-causes of G. There is a bidirectional causality

between G and REN, indicating feedback effects between renewable energy and the FP. Bidirectional causal links are accepted between EC and CO, EF and EC, PT and EC, Y and EC, Y and PT, and Y and EF. Such effects show the existence of further feedback effects among these variables, and the policies should take such effects into consideration. The overall investigation suggests that, through these causal links, the variables are interlinked in various and differentiated settings.; In addition to the rejection of bidirectional links between a set of variables, the accepted unidirectional links can be perceived as evidence of interlinks between the analyzed variables.

Table 6. Granger causality results.

Tested directions and test statistics:					
$\Delta DC \rightarrow$ [1] ΔCO	$\Delta EC \rightarrow \Delta CO$	$\Delta EF \rightarrow \Delta CO$	$\Delta G \rightarrow \Delta CO$	$\Delta PT \rightarrow \Delta CO$	$\Delta G \rightarrow \Delta EC$
$\Delta CO \rightarrow \Delta DC$	$\Delta CO \rightarrow \Delta EC$	$\Delta CO \rightarrow \Delta EF$	$\Delta CO \rightarrow \Delta G$	$\Delta CO \rightarrow \Delta PT$	$\Delta EC \rightarrow \Delta G$
2.815164	3.141356	7.774384	2.472024	4.318899	1.665241
0.206621	10.89310	0.558105	0.511801	0.919536	9.662105
Results:					
$DC \rightarrow CO$	Bidirect.	$EF \rightarrow CO$	$G \rightarrow CO$	$PT \rightarrow CO$	$EC \rightarrow G$
Tested directions and test statistics:					
$\Delta Y \rightarrow \Delta CO$	$\Delta REN \rightarrow \Delta Y$	$\Delta DC \rightarrow \Delta EC$	$\Delta EF \rightarrow \Delta EC$	$\Delta REN \rightarrow \Delta PT$	$\Delta REN \rightarrow \Delta Y$
$\Delta CO \rightarrow \Delta Y$	$\Delta Y \rightarrow \Delta REN$	$\Delta EC \rightarrow \Delta DC$	$\Delta EC \rightarrow \Delta EF$	$\Delta PT \rightarrow \Delta REN$	$\Delta Y \rightarrow \Delta REN$
2.539570	14.63976	10.29339	11.77797	0.587392	4.554488
0.318369	0.655211	0.508830	2.527893	0.252860	0.773745
Results:					
$Y \rightarrow CO$	$REN \rightarrow Y$	$DC \rightarrow EC$	Bidirect.	None	$REN \rightarrow Y$
Tested directions and test statistics:					
$\Delta PT \rightarrow \Delta EC$	$\Delta Y \rightarrow \Delta EC$	$\Delta REN \rightarrow \Delta EC$	$\Delta EEF \rightarrow \Delta DC$	$\Delta G \rightarrow \Delta DC$	$\Delta Y \rightarrow \Delta PT$
$\Delta EC \rightarrow \Delta PT$	$\Delta EC \rightarrow \Delta Y$	$\Delta EC \rightarrow \Delta REN$	$\Delta DC \rightarrow \Delta EF$	$\Delta DC \rightarrow \Delta G$	$\Delta PT \rightarrow \Delta Y$
5.380036	7.434757	2.825914	0.273715	1.137244	2.600277
2.677181	6.970961	0.929427	3.734886	8.339101	8.429795
Results:					
Bidirect.	Bidirect.	$REN \rightarrow EC$	$DC \rightarrow EF$	$DC \rightarrow G$	Bidirect.
Tested directions and test statistics:					
$\Delta REN \rightarrow \Delta DC$	$\Delta Y \rightarrow \Delta DC$	$\Delta PT \rightarrow \Delta DC$	$\Delta G \rightarrow \Delta EF$	$\Delta PT \rightarrow \Delta EF$	$\Delta REN \rightarrow \Delta G$
$\Delta DC \rightarrow \Delta REN$	$\Delta DC \rightarrow \Delta Y$	$\Delta DC \rightarrow \Delta PT$	$\Delta EF \rightarrow \Delta G$	$\Delta EF \rightarrow \Delta PT$	$\Delta G \rightarrow \Delta REN$
1.100649	1.854690	0.251224	0.815937	1.212728	3.563910
3.851204	13.15827	0.20041	5.082487	3.988163	9.647342
Results:					
$DC \rightarrow REN$	$DC \rightarrow Y$	None	$EF \rightarrow G$	$EF \rightarrow PT$	Bidirect.
Tested directions and test statistics:					
$\Delta Y \rightarrow \Delta EF$	$\Delta PT \rightarrow \Delta G$	$\Delta Y \rightarrow \Delta G$	$\Delta REN \rightarrow \Delta EF$		
$\Delta EEF \rightarrow \Delta Y$	$\Delta G \rightarrow \Delta PT$	$\Delta G \rightarrow \Delta Y$	$\Delta EF \rightarrow \Delta REN$		
4.016697	13.73792	8.115728	1.717222		
8.491442	1.849910	1.349080	2.936236		
Results:					
Bidirect.	$PT \rightarrow G$	$Y \rightarrow G$	$EF \rightarrow REN$		

[1] $\rightarrow$ shows the direction of causality; Δ is the first difference operator, and bidirect. refers to bidirectional causality.

Table 7. Nonlinear Granger causality results.

Tested directions and test statistics:					
$\Delta DC^- \to \Delta CO$ [1]	$\Delta DC^+ \to \Delta CO$	$\Delta EC \to \Delta CO$	$\Delta EF \to \Delta CO$	$\Delta G^- \to \Delta CO$	$\Delta G^+ \to \Delta CO$
$\Delta CO \to \Delta DC^-$	$\Delta CO \to \Delta DC^+$	$\Delta CO \to \Delta EC$	$\Delta CO \to \Delta EF$	$\Delta CO \to \Delta G^-$	$\Delta CO \to \Delta G^+$
2.329310	2.526790	5.319346	3.828861	2.509748	2.253622
0.446867	0.860004	6.823491	0.497524	1.100273	0.650206
Results:					
$DC^- \to CO$	$DC^+ \to CO$	Bidirect.	$EF \to CO$	$G^- \to CO$	$G^+ \to CO$
Tested directions and test statistics:					
$\Delta REN \to \Delta CO$	$\Delta Y \to \Delta EC$	$\Delta Y \to \Delta CO$	$\Delta EC \to \Delta DC^-$	$\Delta EF \to \Delta DC^-$	$\Delta G^+ \to \Delta DC^-$
$\Delta CO \to \Delta REN$	$\Delta EC \to \Delta Y$	$\Delta CO \to \Delta Y$	$\Delta DC^- \to \Delta EC$	$\Delta DC^- \to \Delta EF$	$\Delta DC^- \to \Delta G^+$
14.29504	2.290984	2.750666	3.560123	2.604267	2.604267
0.959482	7.032706	0.423376	12.43786	0.992887	6.049183
Results:					
$REN \to CO$	Bidirect.	$Y \to CO$	Bidirect.	$EF \to DC^-$	Bidirect.
Tested directions and test statistics:					
$\Delta PT \to \Delta DC^-$	$\Delta REN \to \Delta DC^-$	$\Delta PT \to \Delta G^-$	$\Delta Y \to \Delta DC^-$	$\Delta EC \to \Delta DC^+$	$\Delta EEF \to \Delta DC^+$
$\Delta DC^- \to \Delta PT$	$\Delta DC^- \to \Delta REN$	$\Delta G^- \to \Delta PT$	$\Delta DC^- \to \Delta Y$	$\Delta DC^+ \to \Delta EC$	$\Delta DC^+ \to \Delta EF$
1.689060	4.875253	2.319762	2.988040	0.360007	0.409736
2.116107	1.041392	0.212623	6.286483	0.336107	1.699191
Results:					
$DC^- \to PT$	$REN \to DC^-$	$PT \to G^-$	$DC^- \to Y$	None	None
Tested directions and test statistics:					
$\Delta G^+ \to \Delta DC^+$	$\Delta PT \to \Delta DC^+$	$\Delta REN \to \Delta DC^+$	$\Delta Y \to \Delta EF$	$\Delta Y \to \Delta DC^+$	$\Delta EF \to \Delta EC$
$\Delta DC^+ \to \Delta G^+$	$\Delta DC^+ \to \Delta PT$	$\Delta DC^+ \to \Delta REN$	$\Delta EEF \to \Delta Y$	$\Delta DC^+ \to \Delta Y$	$\Delta EC \to \Delta EF$
0.384824	0.181267	3.194011	0.341937	0.104523	3.642740
0.065408	3.501476	2.652678	9.155153	1.634021	0.031912
Results:					
None	$DC^+ \to PT$	Bidirectional	$EEF \to Y$	None	$EEF \to EC$
Tested directions and test statistics:					
$\Delta G^+ \to \Delta EC$	$\Delta PT \to \Delta EC$	$\Delta REN \to \Delta EC$	$\Delta PT \to \Delta EF$	$\Delta REN \to \Delta EF$	$\Delta G^- \to \Delta EF$
$\Delta EC \to \Delta G^+$	$\Delta EC \to \Delta PT$	$\Delta EC \to \Delta REN$	$\Delta EF \to \Delta PT$	$\Delta EEF \to \Delta REN$	$\Delta EF \to \Delta G^-$
0.360958	3.564728	2.460026	2.053760	0.075722	2.309468
4.542828	2.845534	1.907207	3.082804	0.270056	12.54967
Results:					
$EC \to G^+$	Bidirectional	$REN \to EC$	Bidirectional	None	$\Delta EF \to \Delta G^-$
Tested directions and test statistics:					
$\Delta Y \to \Delta G^-$	$\Delta PT \to \Delta G^+$	$\Delta REN \to \Delta G^+$	$\Delta Y \to \Delta REN$	$\Delta Y \to \Delta G^+$	$\Delta REN \to \Delta PT$
$\Delta G^- \to \Delta Y$	$\Delta G^+ \to \Delta PT$	$\Delta G^+ \to \Delta REN$	$\Delta REN \to \Delta Y$	$\Delta G^+ \to \Delta Y$	$\Delta PT \to \Delta REN$
14.81911	13.35785	6.167030	1.210487	8.362977	0.114847
0.129225	2.301031	12.63061	4.039794	1.403574	0.996212
Results:					
$Y \to G^-$	$PT \to \Delta G^+$	$G^+ \to REN$	$REN \to Y$	$Y \to G^+$	None
Tested directions and test statistics:					
$\Delta Y \to \Delta PT$	$\Delta PT \to \Delta CO$	$\Delta G^- \to \Delta DC^-$	$\Delta G^- \to \Delta DC^+$		
$\Delta PT \to \Delta Y$	$\Delta CO \to \Delta PT$	$\Delta DC^- \to \Delta G^-$	$\Delta DC^+ \to \Delta G^-$		
1.989750	2.089578	0.403197	0.538303		
8.397586	2.496280	1.128626	7.773570		
Results:					
$PT \to Y$	Bidirect.	None	$DC^+ \to G^-$		
Tested directions and test statistics:					
$\Delta G^- \to \Delta EC$	$\Delta G^+ \to \Delta EF$	$\Delta REN \to \Delta G^-$			
$\Delta EC \to \Delta G^-$	$\Delta EF \to \Delta G^+$	$\Delta G^- \to \Delta REN$			
2.017866	4.050607	6.167030			
15.78133	6.881922	0.889525			
Results:					
$EC \to G^-$	$EF \to G^+$	$\Delta REN \to \Delta G^-$			

[1] $\to$ shows the direction of causality; Δ is the first difference operator, and bidirect. refers to bidirectional causality.

Following the traditional Granger causality results, we present the NBARDL-Granger causality (NBARDL-GC) test results in Table 7. From this approach, we distinguished between expansionary and contractionary MPs measured with G+ and G− variables. The results indicate the causal effects of MPs on CO_2. Such effects are also confirmed for the FP. Both G+ and G− are Granger-causes of CO. Among the energy variables, energy efficiency and renewable energy (EF and REN) had Granger causality effects on CO, while the causal links between fossil fuel energy and CO were bidirectional. Lastly, the bidirectional causal links between Y and EC, EC and DC−, G+ and DC−, and PT and CO could not be rejected from the method that assumed differentiations between expansionary and contractionary policies.

If both the BARDL-GC and NBARDL-GC results are evaluated, significant changes are noted, especially in terms of the asymmetric effects of FPs and MPs. From the novel approach, the causality between each contractionary FP and MP, i.e., G^- and DC^-, could not be accepted, and the same also held for the expansionary policies G^+ and DC^+. All energy variables, REN, EC, and EF, were the causes of G-; however, G^+ Granger caused REN. Furthermore, the analysis confirmed that REN Granger caused Y, indicating the causal effects of renewable energy on economic growth. REN was also the Granger causality of CO_2 emissions and of fossil fuel energy consumption. In return, Y Granger produced CO_2 emissions. The overall investigation of the results indicate significant causal relations between fossil fuel and renewable energy consumption levels, energy efficiency, technology policies, expansionary and contractionary MPs and FPs, economic growth, and CO_2 emissions.

The important results for us can be presented as follows.

- One-way causality from the MP to CO_2; in addition, from contractionary MPs and expansionary MPs to CO_2. Both linear and nonlinear approaches emphasized that MP Granger produced changes in environmental quality.
- One-way causality from the FP to CO_2 and contractionary and expansionary FPs to CO_2. Both approaches showed that the FP has causal effects on the environment.
- The bidirectional causality between EC and CO_2 occurs with both methods.
- Different results were achieved in two approaches: the relationship between technology policies and environmental pollution was found to be different in the two models when evaluated within the framework of technology policies. The linear approach identified a unidirectional causality from PT to CO_2, whereas the nonlinear approach confirmed the existence of a bidirectional causality between the two. Hence, technology policies were the Granger causes of environmental quality.
- Unidirectional, from economic growth to CO_2 emissions in both causality tests; therefore, after assessing the nonlinear effects of MPs and FPs, the results obtained using the traditional Granger causality test confirmed the second approach.
- There was a unidirectional causality from REN to CO_2 in both approaches. Taking nonlinearity into consideration confirmed the results obtained with the linear approach in terms of the direction of causality.
- Lastly, in both approaches, causality was unidirectional, from EF to CO_2. This was a vital finding that confirmed the effects of energy efficiency on CO_2 emissions and, combined with the size of its parameter estimates in the NBARDL model, EF had a relatively greater effect after a 1% upsurge in EF compared to a 1% upsurge in REN. Hence, unless REN was not coupled with EF and technology policies, a commitment to REN would only be inefficient to mitigate environmental degradation.

5. Conclusions and Policy Implications

This study aimed at the examination of simultaneous impacts of technology and energy policies in addition to FPs and MPs by taking the amount of fossil fuel and renewable energy consumption levels and the energy efficiency as factors of energy policies and technology patents on environmental pollution in the USA by applying novel NBARDL and NBARDL-GC causality analyses for a yearly sample covering the years of 1972 and 2022.

The methods utilized in the study benefitted from bootstrapping to overcome degenerate cases of cointegration, and the BARDL model was further augmented with NARDL-type nonlinearity to allow for the examination of asymmetric policy effects. This paper is one of the first studies that utilizes such a model setting. Furthermore, the paper also bridges the gap between two strands of literature: the first is the energy–economic growth environment and the second is the newly emerging MP–FP environment nexus. Furthermore, in this study, energy efficiency, technology, and energy policies are integrated into the models analyzed.

The empirical findings led to important outcomes. According to the findings from the NBARDL results, as the contractionary MP reduces CO_2 emissions, the expansionary MP does the opposite: it is clear that such policies led to upsurges in CO_2 emissions in both the long-run and short run. The interesting discovery of the study is that the FP policy, in an asymmetric setting, has positive effects for both of the expansionary and contractionary FP applications in the economy, confirming the positive influence of FPs on CO_2 not only for expansionary, but also for contractionary FP.

In addition to confirming the above-mentioned impacts of MPs and FPs, resulting in CO_2 upsurges, the findings confirm the positive impacts of fossil fuel energy consumption (EC) and the negative impacts of renewable energy consumption (REN), and these findings are in line with the expectations. However, a striking result of the study regards the energy efficiency (EF). While EC contributes to environmental degradation, among all the remaining energy variables analyzed, EF leads to the greatest CO_2 emission mitigation effect, both in the short and long run, surpassing such mitigation effects of REN. In fact, the long- and short-run coefficients were estimated to be -1.69 and -0.43, respectively, while these figures were calculated as 0.04 for REN in the long and short-run. Hence, unless the large-in-magnitude effect of EF was not adequately taken into focus of energy and technology policies, the policies aiming at accelerating the commitment to REN without being backed-up with strong commitment to EF innovation the achievement of the targets regarding the mitigation of the environmental pollution would be significantly hampered. Therefore, EF should be considered as an important dimension of energy policies and such policies require an effective combination of both the renewable energy and energy efficiency in addition to policies targeting at reducing the fossil-fuel energy consumption.

Our Granger causality findings indicated a one-way causation from the MP to CO_2 emissions, as well as from both contractionary and expansionary MPs to CO_2 emissions. Additionally, we observed evidence of one-way causal links from the FP to CO_2, as well as from both contractionary and expansionary fiscal policies to CO_2. The relationship between technology policies and environmental pollution, when evaluated within the framework of technology policies, was found to be different in the two models. Model 1 identified unidirectional causality from PT to CO_2, whereas the second model confirmed the presence of bidirectional causality between the two. Technology policies have causal effects on environmental pollution. Our results emphasized the one-way causal links from REN to CO_2, as well as from EF to CO_2. According to our results, MPs, FPs, and technology and energy policies play crucial roles in the environmental pollution levels, and policies should further aim at encouraging innovations and investments in EF and clean-energy technologies.

Technology policies are central to reducing environmental pollution by fostering the development, deployment, and adoption of cleaner and more sustainable technologies. Research and development funding in particular is a very important policy instrument. Governments can provide money for R&D technologies that have the potential to minimize pollution and its environmental impact. Modernizing or improving renewable energy technologies, developing methods, enhancing energy efficiency, waste reduction, recycling technologies, and greener industrial processes are examples of these technologies. On the one hand, technology policies could provide financial incentives, grants, or tax credits to businesses and research institutions engaged in developing and commercializing environmentally friendly technologies. Effective technology policies require a mixture of regulatory

measures, incentives, and strategic planning to encourage technological advancements that lead to reduced environmental pollution levels. By fostering an environment conducive to innovation and supporting the adoption of cleaner technologies, governments can make significant contributions to a more sustainable future with less pollution. These policies provide incentives, regulations, and support for the advancement of environmentally friendly solutions.

Monetary and fiscal policies have significant impacts on resource distributions, consumption patterns, and investment decisions. Monetary policies could contribute to reducing environmental pollution levels in different ways. Green bonds and financing are two examples. By providing favorable terms for green bonds, central banks can channel funds towards initiatives that reduce pollution levels. Other methods include interest rates and incentives. Central banks have the authority to modify interest rates or offer favorable lending rates to support investments in clean technologies and ecologically targeted projects. Other monetary policies to be suggested are sustainable banking and investment standards.

Through fiscal policies, governments can also achieve significant impacts on environmental pollution mitigation. Further, the governments must urge all educational and commercial enterprises to incorporate environmental topics into their teaching curricula and training materials [65]. Governments have the ability to provide subsidies and tax advantages to stimulate the adoption of clean energy, enhancements in energy efficiency, and initiatives aimed at reducing pollution levels. A carbon tax or carbon trading system can help the creation of a financial incentive for businesses to reduce their greenhouse gas emissions. Further, fiscal policies could also include pollution fees and charges and subsidies or tax breaks could be given to research and development for cleaner energy and technology investments. Governments can prioritize purchasing environmentally friendly products and services, creating a market demand for sustainable solutions and encouraging industries to adopt cleaner practices. Environmental impact assessments, education and awareness programs should be backed with fiscal policy instruments.

Both monetary and fiscal policies and technology and energy policies have the potential to shape economic activities and implement positive changes for reducing environmental pollution levels. A combination of these policies, along with regulatory measures, can generate a favorable atmosphere for environmental sustainability and pollution mitigation.

On the other hand, as emphasized in many studies, renewable energy consumption reduces environmental pollution levels. Governments can set targets for the acceptance of renewable energy sources, such as wind, hydroelectric, and solar power. They can also provide financial incentives, such as subsidies, tax breaks, and grants, to encourage the progress in the technologies for renewable energies. These policies help shift energy production away from pollution-causing fossil fuels and toward cleaner alternatives. Although the environmental impacts of renewable energy sources are important, the installation costs and environmental problems that may arise during the installation phase, especially during the installation of hydroelectric power plants, are a matter of debate. For this reason, some studies emphasize the importance of EF instead of REN. However, energy policies can also have noteworthy influences on the efficiency of renewable energy. Energy policies can be effectively used in promoting the modernization of the electric grid, making it more adaptable to the integration of renewable energy sources and improving the overall system's efficiency. Governments can develop comprehensive energy transition plans that outline the steps and strategies to shift from fossil fuels to renewable sources over a specific timeline. These plans provide a roadmap for achieving good environmental goals.

Energy policies can establish targets for reducing greenhouse gas emissions and other pollutants. Well-designed energy policies, especially, can encourage the implementation of cleaner and more sustainable sources of energy, the advancement of energy efficiency, and reduce the overall environmental impacts of energy systems. Energy efficiency policies can mandate minimum efficiency standards for appliances, vehicles, and buildings. Regulations can be put in place to limit the emissions from power plants, industrial facilities, and

vehicles. By enforcing stricter emissions standards, governments can force industries to adopt cleaner technologies and practices. Effective energy policies require a combination of regulatory measures, economic incentives, technological advancements, and public engagement. By carefully crafting and implementing such policies, governments can encourage significant reductions in environmental pollution levels and contribute to a more sustainable and cleaner energy future.

The study has a limitation due to restricting the analysis to the USA. Future studies should focus on different countries. In the future, studies are also advocated to focus on energy efficiency in the energy sector in conjunction with technological innovations for clean energies.

Appendix A

As noted in the final part of the Method Section, the method required Granger non-causality tests obtained from a VAR model where the method allowed the integration of asymmetric economic policy responses. The first vector was presented in the Methodology Section for the non-causality test. The remaining vectors of the VAR model are presented below:

$$\Delta Y_t = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=1}^{k} \gamma_i\, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i\, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i\, \Delta REN_{t-i} + \sum_{i=0}^{r} K_i\, \Delta EF_i \qquad \text{(A1)}$$
$$+ \sum_{i=0}^{h} Z_i\, \Delta pt_{t-i} + \zeta_2\, ECM_{t-1} + \varepsilon_t$$

$$\Delta EC_t = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i\, \Delta Y_{t-i} + \sum_{i=1}^{l} \varphi_i\, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i\, \Delta REN_{t-i} + \sum_{i=0}^{r} K_i\, \Delta EF_i \qquad \text{(A2)}$$
$$+ \sum_{i=0}^{h} Z_i\, \Delta PT_{t-i} + \zeta_3\, ECM_{t-1} + \varepsilon_t$$

$$\Delta DC_t^+ = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i\, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i\, \Delta EC_{t-i} + \sum_{i=1}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i\, \Delta REN_{t-i} + \sum_{i=0}^{r} K_i\, \Delta EF_i \qquad \text{(A3)}$$
$$+ \sum_{i=0}^{h} Z_i\, \Delta PT_{t-i} + \zeta_4\, ECM_{t-1} + \varepsilon_t$$

$$\Delta DC_t^- = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=1}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i \, \Delta REN_{t-i} + \sum_{i=0}^{r} K_i \, \Delta EF_i \qquad (A4)$$
$$+ \sum_{i=0}^{h} Z_i \, \Delta PT_{t-i} + \zeta_5 \, ECM_{t-1} + \varepsilon_t$$

$$\Delta G_t^- = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=1}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \qquad (A5)$$
$$\sum_{i=0}^{q} A_i \, \Delta REN_{t-i} + \sum_{i=0}^{r} K_i \, \Delta EF_i + \sum_{i=0}^{h} Z_i \, \Delta PT_{t-i} + \zeta_6 \, ECM_{t-1} + \varepsilon_t$$

$$\Delta G_t^+ = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=1}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i \, \Delta REN_{t-i} \qquad (A6)$$
$$+ \sum_{i=0}^{r} K_i \, \Delta EF_i + \sum_{i=0}^{h} Z_i \, \Delta PT_{t-i} + \zeta_7 \, ECM_{t-1} + \varepsilon_t$$

$$\Delta REN_t = c + \sum_{i=0}^{m} B_i \Delta co_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+$$
$$+ \sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=1}^{q} A_i \, \Delta REN_{t-i} \qquad (A7)$$
$$+ \sum_{i=0}^{r} K_i \, \Delta EF_i + \sum_{i=0}^{h} Z_i \, \Delta PT_{t-i} + \zeta_8 \, ECM_{t-1} + \varepsilon_t$$

$$\Delta EF_t = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+$$
$$+ \sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i \, \Delta REN_{t-i} \qquad (A8)$$
$$+ \sum_{i=1}^{r} K_i \, \Delta EF_i + \sum_{i=0}^{h} Z_i \, \Delta PT_{t-i} + \zeta_9 \, ECM_{t-1} + \varepsilon_t$$

$$\Delta PT_t = c + \sum_{i=0}^{m} B_i \Delta CO_{t-i} + \sum_{i=0}^{k} \gamma_i \, \Delta Y_{t-i} + \sum_{i=0}^{l} \varphi_i \, \Delta EC_{t-i} + \sum_{i=0}^{p} \lambda_i^+ \Delta DC_{t-i}^+ +$$
$$\sum_{i=0}^{n} \lambda_i^- \Delta DC_{t-i}^- + \sum_{i=0}^{z} \delta_i^- \Delta G_{t-i}^- + \sum_{i=0}^{f} \delta_i^+ \Delta G_{t-i}^+ + \sum_{i=0}^{q} A_i \, \Delta REN_{t-i} \qquad (A9)$$
$$+ \sum_{i=0}^{r} K_i \, \Delta EF_i + \sum_{i=1}^{h} Z_i \, \Delta PT_{t-i} + \zeta_{10} \, ECM_{t-1} + \varepsilon_t$$

where ζ_j, $j = 1,2, \ldots, j$ are the ECM parameters indicating the convergence speed to the long-run equilibrium relation after a shock. For the model of this study, $j = 10$, ECM term was derived from the NBARDL long-run specification. The ECM coefficients define the speed of convergence to the long-run equilibrium in each vector with the following necessary conditions for each ζ_j: a statistical significance of ζ_j; non-positive parameter estimates so that $\zeta_j < 0$ for ζ_j $j = 1, 2, \ldots, j$; $-1 < \zeta_j < 0$ being estimated between -1 and 0. Hence, the speed of convergence was $1/\zeta_j$ years, in absolute terms. For the NBARDL-GC causality testing procedure, we refer the readers to [21].

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