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Does economic policy uncertainty, energy transition and ecological innovation affect environmental degradation in the United States?

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ABSTRACT

Climate change traps heat, affecting a variety of species in already dry areas. Severe storms, earthquakes, plagues, and food delivery problems are all exacerbated by climate change caused by emissions of greenhouse gases. The United States, the world's largest economy and second-largest carbon emitter is expertly planning to reduce its environmental difficulties and help the accomplishment of the United Nations Sustainable Development Goals (SDGs) 7 and 13. Given that, the study explores the renewable energy transition, ecological innovation, economic policy uncertainty, and globalization from 1990 to 2019 by using novel econometric approaches augmented ARDL and gradual shift causality. The results show that variables are cointegrated, particularly in the long and short term; renewable energy transition and economic policy uncertainty reduce carbon emissions, while ecological innovation contributes to long-run depletion in CO_2 emission. Globalization significantly accelerates emissions in the long and short term. Furthermore, gradual shift causation reveals that renewable energy transition and globalization are unidirectional, but economic policy uncertainty is bidirectional. Finally, the conclusion implies that transitioning from fossil to renewable energy, adequate use of technology, efficient management of policy uncertainties and globalization may contribute to the United States meeting SDGs 7 and 13.

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Abbreviations: AARDL: Augmented Autoregressive Distributed Lag; ADF: Augmented Dickey-Fuller; CF: cumulative frequencies; CO_2: carbon dioxide; ECT: error correction term; EI: ecological innovation; EKC: Environmental Kuznets curve; EPU: economic policy uncertainty; GHGs: greenhouse gases; GMM: generalised method of moments; KPSS: Kwiatkowski, Phillips, Schmidt, and

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Shin; kt: kilotons; MENA: Middle East/North Africa; NAFTA: North American Free Trade Agreement; PP: Phillips-Perron; RE: renewable energy; SSA: Sub-Saharan Africa; USA: United States of America

1. Introduction

It is glaringly clear that environmental degradation has now become one of the most disturbing challenges facing the world today. This is not farfetched, looking at the continued rise in carbon dioxide (CO_2) emissions from greenhouse gases (GHGs) despite the anticipated repercussions of unchecked climate change. Thus, the unprecedented rise in desertification, unpredictable precipitation patterns and temperatures, and extreme weather could make many regions of the world inhabitable (OECD, 2019). The threats of climate change are multiple and interlinked with other environmental problems, including biodiversity loss and other associated ecosystems, waste generation, and rising air and water pollution (Sadoff et al., 2015). To circumvent these challenges, world leaders initiated a policy action in the form of SDGs to be achieved by the end of 2030 and the celebrated Paris Agreement on Climate Change to solve the problem of climate change and its negative consequences. Specifically, the policy action is saddled with the responsibility of not allowing the increase of greenhouse gas emissions up to 2 degrees Celsius with design strategies to decrease it further to even 1.5 °C (Abbasi et al., 2022c; United-Nations, 2015).

With an approximately 1.0 °C climate change in the United States, its devastating effects are already alarming, affecting the vulnerable people in most communities with a climate-fuelled catastrophe that led to deaths, degraded health, poor standard of living, and even destruction of earth's ecosystem. Therefore, there is an urgent need to address the climate crisis by transforming the fossil fuel-dominated energy sector to a renewable energy-based sector to achieve the goals of SDG7 as well as the objectives of the Paris Agreement of the decarbonised energy system (USDS, 2021). Interestingly, the UN (2021) estimates unravelled that the solutions in 2050 will revolve around renewable energy transition that can be achieved through direct supply electrification, increasing energy efficiency, and green hydrogen. Simultaneously, massive efforts in bioenergy with carbon capture and storage, nuclear energy, and fossil carbon capture and storage will play significant roles, especially when policymakers have taken ecological and political uncertainties. However, identifying measures for mitigating CO_2 emissions without hampering economic growth has been a daunting task, which is why Abbasi et al. (2022b) and Zhao et al. (2022) posited that any portfolio of mitigating technology to be adopted must be critically evaluated in terms of its sustainable development capacity and other associated consequences.

Globalization stimulates developing and developed countries' economic growth and development through reciprocal dependency on international trade, capital flow, foreign aid, and ecological innovation. However, it is not without negative externalities that would degrade the environmental quality (Akadiri et al., 2022). Similarly, the inability to predict the potential economic outcomes of government policies by most economic agents has attracted the interest of scholars in energy and environmental economics. This is because economic policy uncertainty affects the environment where such economic entities operate, and any changes may likely influence their decisions that would, in turn, stimulate or retard CO_2 emissions (Liu & Zhang, 2022). The unprecedented rise of energy consumption in the United States led to a surge in CO_2 emissions, which in turn influences policy changes in energy consumption and climate change; recent among them is the US rejoined of the Paris Agreement in order to achieve the objectives of SDG 7 and 13 of seamless transition of renewable energy consumption and achieve environmental sustainability (Awan et al., 2022; Raza et al., 2022) and (USDS, 2021). Against the above backdrop, exploring the role of the renewable energy transition, ecological innovation, globalization, and CO_2 emission in the USA is required from the lens of economic policy uncertainty.

Thus, our research contributes to the body of prior literature in the following ways. **First,** in order to objectify the ambitious goal of Nationally Determined Contribution (NDC) in the United States, reducing GHG emissions by 50–52% in 2030, findings from this study will shed some light on the implications of the economic policy uncertainty within the context of the renewable energy transition, ecological innovation, globalization, and CO_2 emissions. **Second**, the current study departs from the previous studies by utilising the Augmented Autoregressive Distributed Lag (AARDL) model proposed by Sam et al. (2019). This technique is preferred over the conventional cointegration tests because relying on traditional ARDL, as argued by Cai et al. (2018) may produce spurious results. This is convincingly demonstrated by McNown et al. (2018) that the cointegration test should be tested against all three tests rather than relying on the overall F-statistics. The augmented ARDL overcomes this shortcoming by introducing an F-test on the explanatory variables' lagged level and the capacity to accommodate the degenerate cases. This is because degenerate cases may lead to the wrong conclusion about the absence of cointegration among the studied variables (Hossain et al., 2022). Specifically, in the words of Goh et al. (2017), augmented ARDL introduced a new test capable of finding the exact cointegration relationship among the variables. **Third,** findings from this study would not only assist in formulating SDG-oriented policies that would ensure net-zero GHG emissions by 2050 but also strengthen the overarching goal of developing a more robust and sustainable economy.

The rest of the study is configured into the following sections: A review of the related literature is stationed in Section 2. The detailed methodology of the study is discussed in Section 3, while presentations of empirical results with their discussions are provided in Section 4. Section 5 focuses on the conclusion and policy implications of the study.

2. Literature review

2.1. Renewable energy transition and environment

Environmental degradation has been considered one of the monumental challenges threatening future generations. As a result, studies identified renewable energy transition as one of the most effective and efficient ways of improving and strengthening environmental quality. Therefore, Sharif et al. (2020) used a quantile ARDL to assess the effect of renewable energy consumption and nonrenewable energy usage on the ecological footprint in Turkey and reported that renewable energy usage reduces the ecological footprint. However, the findings suggested that nonrenewable energy usage and economic expansion stimulate ecological footprint. Using a bootstrapping ARDL methodology within a STIRPAT in Turkey, Shan et al. (2021) concluded that renewable energy usage and green technology strengthen environmental quality. But, nonrenewable energy usage, population, and income negatively affected environmental quality. Radulescu et al. (2022) examined the renewable energy and economic expansion on the environmental footprint of 27 OECD nations using data from 1990 and 2018. The findings showed that renewable energy encourages ecological sustainability using the moments' quantile regression (MMQR) approach. Similarly, Romania (Rehman et al., 2022) used the Autoregressive Distributed Lag (ARDL) approach in combination with FMOLS (Fully Modified Least Squares) and CCR (Canonical Cointegrating Regression).

Further, Rej et al. (2022b) used the unique dynamic ARDL and augmented ARDL co-integration method to examine the effects of exports, renewable energy, and industrialization on India's ecological footprint from 1970 to 2017. The empirical findings show that industrialization increases the EF while exports and the use of renewable energy decrease. Rej et al. (2022a) adopted the "non-linear autoregressive distributed lag" model and spectral causality for India from 1999 to 2018. Their outcome indicated that economic growth has a negative long-term and short-term influence on the environment. While technology innovation has a long-term detrimental influence on environmental quality. Focusing on Sweden with the quantile-on-quantile technique, Adebayo et al. (2021) explored the asymmetric effect of renewable energy usage on CO_2 emissions by controlling for trade openness and established that in most of the quantiles, renewable energy usage, income, and trade openness retard environmental degradation. A recent study by Awosusi et al. (2022) utilised a gradual shift technique and conventional ARDL to study the influence of renewable energy usage and globalization on CO_2 emissions in Columbia by controlling for economic expansion and natural resources. The outcome showed that renewable energy usage and globalization improve environmental quality in the long run. However, the study evidenced that economic expansion increases environmental degradation.

Similar to country-specific studies, evidence from the multi-country framework has also been conducted. For instance, Inglesi-Lotz and Dogan (2018) used a mean group DOLS to explore the influence of renewable energy usage on CO_2 emissions in the ten most generating electricity countries in SSA by controlling for nonrenewable energy usage, income, and trade openness and documented that renewable energy usage and trade openness improve environmental quality. However, the outcome of nonrenewable energy usage retards environmental quality and that of income upheld the EKC hypothesis. A similar methodology (Destek & Sinha, 2020) employed mean group regression to assess the effect of renewable energy usage, nonrenewable energy usage, trade openness and income in 24 OECD countries and showed that renewable and nonrenewable energy usage stimulates and retard environmental quality, respectively. Also, the outcome unravelled the existence of the EKC hypothesis. Also, another study on BRICS economies (Danish et al., 2020a) used fully modified OLS and dynamic OLS to unravel the influence of renewable energy usage on ecological footprint by controlling for natural resources and urbanization and found that renewable energy usage, natural resources and urbanization retard ecological footprint.

Structuring the countries from the lens of income group and evaluating the nexus between disaggregate energy utilization and CO_2 emissions in 102 countries. Le et al. (2020) employed static and dynamic panel techniques and demonstrated that renewable energy usage retards environmental degradation. However, nonrenewable energy usage showed a harmful effect on environmental quality. A more recent study with a quantile methodology by Olanrewaju et al. (2022) assessed the interaction between renewable energy usage and CO_2 emissions in G7 countries controlled by eco-innovation, trade openness, income and nonrenewable energy usage and established a strengthened impact of renewable energy utilization on environmental quality in lower and upper quantiles. Similarly, the outcome of eco-innovation and income improves environmental quality. However, nonrenewable energy utilization and trade openness showed a detrimental effect on the environment.

2.2. Ecological innovation and environment

A successful transition from a dirty to a cleaner environment depends on the ecological innovation ability of a given country. Thus, Ali et al. (2016) investigated the extent to which technological innovation determines CO_2 emissions in Malaysia by controlling for economic growth and financial development. The outcome justified an insignificant effect of technological innovation on CO_2 emissions. Although the outcome of economic growth upheld the EKC hypothesis, financial development retards environmental degradation. A similar study by Yii and Geetha (2017) applied the traditional ARDL and Toda and Yamamoto to study the extent to which technological innovation determines CO_2 emissions in Malaysia and showed that technological innovation stimulates environmental quality while income and its square exerted a positive and negative effect on CO_2 emissions, respectively. Usman and Radulescu (2022) used cutting-edge panel data techniques, including the AMG and CCEMG estimation method. Environmental quality is strongly protected by nuclear and renewable energy. Technological advancements, using natural resources, and non-renewable energy sources harm the environment.

In a wavelet effect analysis of innovation in technology and renewable energy usage on environmental degradation in Portugal, Adebayo et al. (2021) established that technological innovation and renewable energy usage retard and stimulate environmental degradation, respectively. A recent study conducted in Pakistan by Abbasi et al. (2022a) employed novel dynamic ARDL simulations to find out the extent to which ecological innovation and financial development influence environmental degradation proxies by consumption and territory-based emissions and discovered that financial development stimulates environmental degradation for both proxies. However, the study's outcome documented that ecological innovation retard environmental degradation.

Multi-country studies also investigated the nexus between ecological innovation and the environment, but their findings' consensus is yet to be obtained. For example, Zhang (2021) explored the influence of ecological innovation and economic growth with the STIRPAT framework for BRICS member countries. The study utilised a static panel methodology and revealed that ecological innovation influences environmental quality. However, the study's outcome documented an adverse effect of economic growth on environmental quality. In another study of 35 OECD countries, Cheng et al. (2021) used a panel quantile regression to study the extent to which the direct and moderating influence of technological innovation on CO_2 emissions and unravel the negative heterogeneous effect of technological innovation on CO_2 emissions, in addition to upholding the EKC hypothesis. Similarly, the study evidenced that renewable energy utilization and investment improve environmental quality.

Obobisa et al. (2022) focused on 25 African countries by utilising augmented mean group and common correlated mean group to explore the effect of green technological innovation, renewable energy utilization, and institutional quality on CO_2 emissions and established that green innovation, technological invention and renewable energy usage stimulate environmental quality. However, income, nonrenewable energy usage, and the institutional quality confirmed a disastrous influence on environmental quality. A similar recent study by Rahman et al. (2022) in their attempt to study the extent to which technological innovation affects CO_2 emissions in 22 countries in addition to renewable energy usage and export quality via the application of non-linear ARDL and established that negative shock of technological innovation, in the long run, stimulate CO_2 emissions. But, the study found that renewable energy usage improves environmental quality. The outcome also documented that positive and negative shocks stimulate and retard CO_2 emissions.

2.3. Economic policy uncertainty and environment

The rate at which a country or region will deploy CO_2 emissions abatement technologies to a certain extent depends on economic policy uncertainties. As such, studies have been conducted from both time series and panel perspectives. For example, a study by Festus Fatai Adedoyin (2020) utilised the conventional ARDL on the UK economy to unravel the extent to which economic policy uncertainty determines environmental degradation by controlling for economic expansion and energy usage and documented insignificant negative and positive effects of economic policy uncertainty on the environment in short and long run, respectively. Energy usage also displayed a similar but significant impact on environmental degradation. However, income is found to have significantly improved the environment. But, Xue et al. (2022) utilised the novel augmented ARDL technique to discover the effect of economic policy uncertainty on CO_2 emissions in France and established that economic policy uncertainty degraded the environment in the long run.

Focusing on China (Abbasi & Adedoyin, 2021) unravelled how economic policy uncertainty affects CO_2 emissions by controlling for energy usage and economic growth and reported that economic policy uncertainty does not affect CO_2 emissions.

However, the study concluded that energy use and economic growth retard the environment not only in the short but also long run. But, using the celebrated dynamic ARDL simulations (Amin & Dogan, 2021) unravelled the nature of the role played by economic policy uncertainty determining environmental degradation in China in addition to income, energy intensity population and economic structure. The outcome established the adverse effect of uncertain economic policy on the environment. Similarly, income, population and energy intensity exert a disastrous effect on the environment. However, the study concluded that economic structure stimulates environmental quality.

Using balanced panel data for 30 provinces spanning 2003–2017, Liu and Zhang (2022) studied the extent to which uncertain economic policy affects CO_2 emissions and demonstrated that economic policy uncertainty improves environmental quality. However, the study established that environmental regulations and energy usage degrade environmental quality. However, a recent study by Fu et al. (2022) studied how uncertainty in economic policy influences CO_2 emissions at the Chinese city level and concluded that any rise in economic policy uncertainty would stimulate CO_2 emissions.

Zakari et al. (2021) investigated the extent to which uncertainty in economic policy effects CO_2 emissions in 22 OECD countries by controlling for energy use and economic growth. The study used PMG-ARDL and documented that uncertain economic policy stimulates CO_2 emissions in the long run. But, the study established that energy use and economic growth retard environmental quality in the short run. Focusing on the BRICS member countries, Hussain et al. (2022) explored the capacity of economic policy uncertainty in determining the level of environmental quality via the application of second-generation unit root and cointegration methodologies and demonstrated that economic policy uncertainty stimulates environmental quality. However, energy structure and related technologies played a disastrous role in environmental quality.

Furthermore, Zhou et al. (2022) considered the five most polluted economies and studied the extent to which uncertain economic policy impacts CO_2 emissions by controlling for renewable energy, income and environmental technologies and discovered that economic policy uncertainty degraded environmental quality. However, all control variables are found to have stimulated the environmental quality. Using a GMM model on 137 countries, Su et al. (2022) studied the influence of uncertain economic policy on environmental performance covering 2001–2018 and disclosed that economic policy uncertainty retards environmental performance. Also, Khan et al. (2022), in a study of five eastern economies, applied a panel dynamic seemingly unrelated regression to study the extent to which economic policy uncertainty affects CO_2 emissions and concluded that economic policy uncertainty harmfully affects environmental quality.

2.4. Globalization and environment

The question of whether globalization may affect the environment has been examined in the environmental economics literature, but conflicting outcomes are still unfolding. Salahuddin et al. (2019) utilised ARDL bound test to explore the effect of globalization and urbanization on CO_2 emissions in South Africa by controlling for energy poverty and income. The study's outcome established that globalization has no significant effect on CO_2 emissions. However, the outcome documented that urbanization improves environmental quality. However, Oladipupo et al. (2022) utilised a quantile-on-quantile technique to study the extent to which globalization influences CO_2 emissions in South Africa and confirmed the detrimental effect of globalization on CO_2 emissions. Similarly, nonrenewable energy usage and economic expansion deteriorate CO_2 emissions.

Evidence from a cross-country study was also conducted but documented a conflicting outcome. For instance, Kalaycı and Hayaloğlu (2019) investigated the influence of economic globalization on CO_2 emissions in NAFTA member countries and confirmed the detrimental effect of globalization trade openness on environmental quality. Similarly, the outcome of the study upheld the EKC hypothesis. Using a second-generation framework, He et al. (2021) studied the extent to which globalization moderated by economic complexity affects CO_2 emissions in top-ten energy transition countries. The study applied CS-ARDL and discovered that globalization, economic complexity and renewable usage retard environmental degradation.

In addition, Xiaoman et al. (2021) utilised the continuously updated, fully modified and continuously updated bias-corrected methodologies to assess the effect of natural resource abundance, globalization, trade openness, income, and urbanization on CO_2 emissions of MENA countries. The outcome revealed that natural resource abundance and globalization improve environmental quality. However, the study confirmed the harmful effect of urbanization, trade openness and income on environmental quality. Lenz and Fajdetic (2021) studied the connection between globalization and CO_2 emissions by selecting 26 EU member countries via the application of difference GMM and showed that globalization has an adverse effect on CO_2 emissions. A similar methodology is adopted by Yameogo et al. (2021) studied the extent to which economic globalization induces environmental quality in 20 SSA countries. The study utilised the GMM technique and established that economic globalization improves environmental quality. However, institutional variables are found to have significantly degraded environments.

Furthermore, Xue et al. (2021) studied the four selected South Asian countries with the aid of dynamic common correlated effects to unravel how globalization affected CO_2 emissions and documented a harmful effect on CO_2 emissions. In another recent study, Li et al. (2022) studied the effect of globalization on CO_2 emissions in MINT countries in addition to technological innovation and green investment and demonstrated that globalization green investment stimulates environmental quality. However, ecological innovation, income, and nonrenewable energy usage deteriorate environmental quality. Also, Bilal et al. (2022) studied the duo effect of green ecological innovation and globalization on CO_2 emissions in One Belt One Road countries and concluded that globalization rouses CO_2 emissions. However, green ecological innovation improves environmental quality.

2.5. Research gap

Existing studies unravelled the co-movement and causal relationships between the variables and established a conflicting outcome in the environmental economics literature. It is worthy of note to stress that very few studies explored the role of

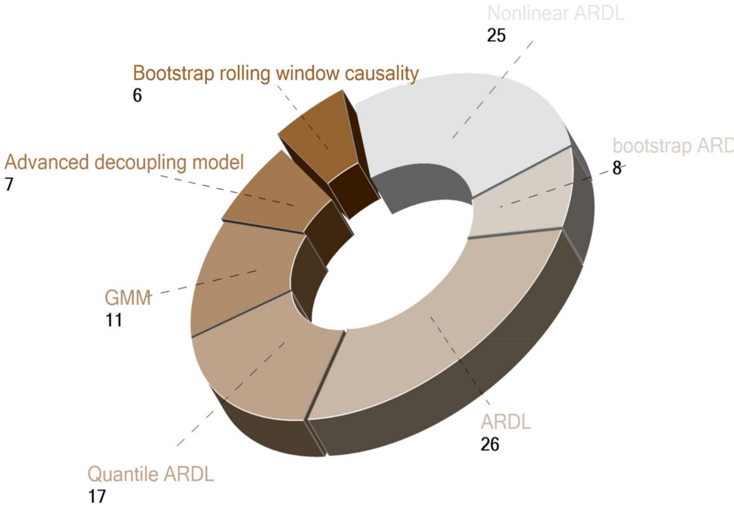

Figure 1. Studies conducted in the USA with their methodology.
Source: Author's own estimation.

economic policy uncertainty in determining environmental quality in the USA with inconclusive results. Therefore, this study extends the literature by examining the nexus among renewable energy transition, ecological innovation, globalization, and CO_2 emission in the USA from the lens of economic policy uncertainty. As per a thorough investigation of the earlier studies, Figure 1 summarises that in the US, most studies applied Nonlinear ARDL, bootstrap ARDL, ARDL, Quantile ARDL, GMM, Advanced decoupling model and Bootstrap rolling window causality with different factors of the environment. However, the current study also departs from the previous studies conducted in the USA by employing the novel augmented ARDL developed by Sam et al. (2019). This technique is chosen because of its ability to detect exact cointegration among the variables. It can also handle the problems of endogeneity, autocorrelation, and small sample bias. Another interesting advantage is not only relying on the overall F-statistics; the technique also inspects cointegration from the explanatory and explained variables with the aid of F-statistics and t-statistics, respectively. Finally, the study addressed the identified lacuna with the SDG 7 and 13 oriented policy recommendation.

3. Econometric methodology

3.1. Data sources and variable justification

This study uses yearly data gathered from 1990 to 2019 for a comprehensive sample of the United States for which data is accessible. Furthermore, the sample determination is solely based on data availability, suitability, model specifications, and making key policy suggestions for the United States. The United States is the world's second greatest polluter, emitting 4.7 billion metric tonnes of carbon dioxide in 2020. Nonetheless, being the world's second-largest polluter, the United States emissions have lessened by 16 percent since 2010 (Statista, 2020). CO_2 emissions are a gigantic problem for the planet since emissions have amplified by more than 100% in the previous three decades.

Table 1. Data and sources.

Determinants	Sources	Measurement Unit
CO_2 emissions	WDI (2019)	kilotons (kt)
Renewable Energy Transmission	WDI (2019)	(% of total final energy consumption)
Ecological Innovation	WDI (2019)	Patent applications (resident + non-resident)
Economic Policy Uncertainty	EPU (2019)	Numbers in Year
Globalization	KOF (2019)	KOF index

Source: Author's own estimation.

Consequently, policymakers have made prompt evolution toward an energy transition. Hence, the study chosen appropriate variables in this analysis are as follows:

CO_2 emissions are measured in kilotons (kt). The figures are derived from the use of fossil fuels as energy sources and the production of cement. This variable comprises CO_2 emissions from solid and liquid fossil fuels. The variable RE denotes the proportion of renewables in total final energy consumption estimates, which is intended to approximate the scope of RET. Because RET is anticipated to lower CO_2 emissions (Koengkan & Alberto Fuinhas, 2020).

Additionally, ecological innovation (EI) helps reduce pollutants, thereby saving energy. Also, EI is essential for the optimal usage of renewable energy (RE) and conventional sources. TI may also assist in the development of new RE sources. TI also enhances RE capacities, improving the chance of RE supply meeting prospective energy demand. Given the ever-increasing need for energy, many people believe that RE will be the most important energy source and an ecologically safe form of energy; hence, ecological innovation uses the proxy of patent applications (resident + non-resident).

The study's major goal is to link the energy-environmental link to strategy uncertainty. In doing so, we employ Baker et al.'s (2016) index of U.S. economic policy uncertainty, which is based on a weighted average of three components: policy-related news reporting, the number of federal tax code provisions set to expire in coming years, and dissent among institutional forecasting models.

Furthermore, the theoretical foundation for the relationship between CO_2 emissions and globalization is simple: as nations get more globalised, so does their energy demand. It is often expected that trade impediments would fall as globalization develops, increasing a country's production and income. An increase in energy usage is connected with an increase in output and revenue. Because it is often considered that more globalization is related to greater levels of economic development, it is also widely assumed that globalization assists in mitigating environmental degradation; otherwise, it would promote environmental deterioration if not eco-friendly. Table 1 clarifies the data sources and measurements (Figure 2).

Figure 2 illustrates the stepwise methodological framework of the study.

3.2. Unit root inspection

First and foremost, before estimating the augmented ARDL model, we utilised numerous unit root tests to ensure the stationarity of the data, such as the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP), and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS). Additionally, Lee and Strazicich (2013) applied to address the shortcomings of traditional unit root tests such as the (ADF, PP and

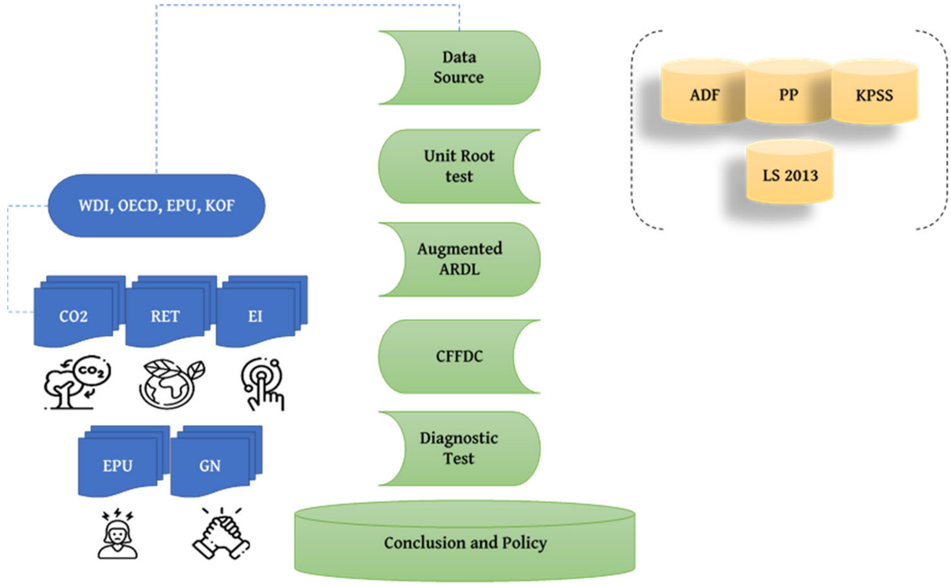

Figure 2. Pictorial view of methodology.
Source: Author's own estimation.

KPSS). The Lee and Strazicich, (2013) unit root test is a one-structural-break minimal Lagrange multiplier (LM) unit root test. In comparison to previous structural break tests, such as the Clemente et al. (1998), Lumsdaine and Papell (1997), and Zivot and Andrews (1992) tests, the Lee and Strazicich, (2013) test has a superior size and strength features, as well as the ability to determine break dates more reliably. As a result, using the Lee and Strazicich, (2013) test removes the threat of wrong calculations and break date forecasts. For the unit root testing, the null hypothesis is H0 $\varphi = 0$, which is tested against the alternative H1: $\varphi < 0$.

3.3. Augmented ARDL bounds test

To analyse the effects of the renewable energy transition, ecological innovation, economic policy uncertainty, and globalization on CO_2 emissions in the United States, this study employs augmented ARDL bounds testing approach to the cointegration suggested by Sam et al. (2019). Though several cointegration approaches exist, including those developed by Engle and Granger (1987), Johansen (1988), and Søren Johansen (1990), these models are not appropriate unless the data series has a distinct order of integration. In comparison, the ARDL model is more versatile in terms of the application when data series lack a specific integration sequence. This model may be used for variables with unlike integration orders, including I(0) and I. (1). However, it is inadequate if any of the variables is I.(2) {Formatting Citation}. Furthermore, it could be applied systematically to a small dataset to generate reliable results (Haug, 2002). Besides, when a lag selection is embraced for both the explained and explanatory factors, it gives additional prospects and is apt to cope with any endogeneity issues that may occur in variables.

The ARDL model is certainly popular among researchers. McNown et al. (2018) and Sam et al. (2019) stated that this test is pretty flexible since it allows the control variables to be I(0) or I(1) if the response variable is I(1). Notably, most researchers (Pesaran et al., 2001) ignored the requirement that the response variable be I(1). As a result, erroneous outcomes are produced, resulting in the defective examples noted by Sam et al. (2019). To tackle this issue, McNown et al. (2018) and Sam et al. (2019) enhanced the ARDL model created by Pesaran et al. (2001), referring to it as the augmented ARDL. Moreover, they recommended the F-test for explanatory variables as an alternative to the F-test and t-test. An extra t-test or F-test for the coefficients of lagged explanatory variables utilised in this model.

In contrast, Goh and McNown (2015) demonstrated that using just the F-test and t-test statistics for the total lagged dependent variables was insufficient for the ARDL model. To exclude the degenerated case-1 found by Pesaran et al. (2001) and subsequently by McNown et al. (2018), a second t-test or F-test on the lagged explanatory factors concerning the ARDL test was presented. To distinguish between cointegration and degenerate circumstances, all three criteria must be used to validate the cointegration relation directly. The model is described in the following manner:

$$\Delta CO2_t = \alpha_1 + \sum_{i=1}^{p} \beta_1 \Delta CO2_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta RET_{t-i} + \sum_{i=0}^{r} \beta_3 \Delta EI_{t-i} + \sum_{i=0}^{s} \beta_4 \Delta EPU_{t-i} + \sum_{i=0}^{t} \beta_5 \Delta GN_{t-i} + \gamma_1 CO2_{t-i} + \gamma_2 RET_{t-i} + \gamma_3 EI_{t-i} + \gamma_4 EPU_{t-i} + \gamma_5 GN_{t-i} + \sigma_1 D_t + \varepsilon_t \tag{1}$$

where ε_t represents white noise error and symbolises the first difference. While aggregate reflects short-run dynamics, and $\gamma_1 - \gamma_5$ for long-run events. D_t is appended to the dataset to accommodate for any structural irregularities. In this instance, the H0 is $\gamma_1 = \gamma_2 = 0$, suggesting that there is no long-run link. The primary test in the ARDL modelling research is an F-test to measure the cumulative impact of the level parameters (Pesaran et al., 2001, 1999). The second test for the lagged explained variables is a t-test. Whether the regressors are I(0) or I(1), the values below the H0 reveal a non-standardised distribution in the absence of a level affiliation.

Despite employing standard critical values, Pesaran et al. (2001) and Sam et al. (2019) proposed two sets of approximation critical values: one for purely I(1) regressors and the other for fully I(0) regressors. If the F-test and t-test statistics are less than the lower limit critical value, the H0 of "no long connection" cannot be rejected. Clearly shows that there is no long-run relationship between the variables. In contrast, if the F-test and t-test statistic values surpassed the upper limit critical value, the H0 would be disregarded. It indicated the presence of long relationships between the parameters. Finally, if the test statistic's value was neither less than nor greater than the two critical values, showing that the value fell between the two critical values, the conclusion regarding the long-run correlations remained uncertain. The error correction model (ECM) for evaluating short-run features is as regards:

$$\Delta CO2_t = \alpha_1 + \sum_{i=1}^{p} \theta_1 \Delta CO2_{t-i} + \sum_{i=0}^{q} \theta_2 \Delta RET_{t-i} + \sum_{i=0}^{r} \theta_3 \Delta EI_{t-i} + \sum_{i=0}^{s} \theta_4 \Delta EPU_{t-i} + \sum_{i=0}^{t} \theta_5 \Delta GN_{t-i} + \omega ECT_{t-1} + \mu_t \quad (2)$$

Where θ_5 = denotes short-run inefficiencies, ECT is the error correction term that measures the rate at which each period returns to equilibrium following a shock, and is the corresponding parameter that offers an estimate. The expected value of the ECT parameter is between −1 and 0, with 0 indicating no divergence toward equilibrium and 1 representing perfect convergence, which implies that if the value is −1, any shock in the given period is properly adjusted in the following period. The following three test statistics were employed to demonstrate the cointegration relationship:

$$F_{overll}^{test} H_0 : \emptyset_1 = \emptyset_2 = \emptyset_3 = \emptyset_4 = 0 \quad (3)$$

$$t_{DV}^{test} H_0 : \emptyset_1 = 0 \quad (4)$$

$$F_{IDV}^{test} H_0 : \ \emptyset_2 = \emptyset_3 = \emptyset_4 = 0 \quad (5)$$

The tests specified in Eqs. (3) and (4) are the F-test and t-test, as proposed by Pesaran et al. (2001). Simultaneously, Eq. (5) denotes a new F-test presented by McNown et al. (2018) and Sam et al. (2019). To prove cointegration, the three tests must be bigger than the critical values and statically significant. If not, the cointegration relationship would be inaccurate. Degenerate case 1 arises if both the generalised F-statistic and the t-statistic are significant, but the F-independent statistics are not. The degenerate condition is described as 2 when both the F- and t-statistics are significant.

3.4. Augmented autoregressive distributed lag model

In this research, the ARDL framework scrutinises the effects of the renewable energy transition, ecological innovation, economic policy uncertainty, and globalization on CO_2 emissions in the United States. The ARDL model is estimated in two methods. First, the co-integration test ARDL model determines whether or not there is a long-term causal link between the variables by using the following model:

$$\Delta CO2_t = \beta_0 + \beta_1 CO2_{t-1} + \beta_2 RET_{t-1} + \beta_3 EI_{t-1} + \beta_4 EPU_{t-1} + \beta_5 GN_{t-1} + \sum_{i=1}^{a} \beta_6 CO2_{t-i} + \sum_{i=1}^{b} \beta_7 RET_{t-i} + \sum_{i=1}^{c} \beta_8 EI_{t-i} + \sum_{i=1}^{d} \beta_9 EPU_{t-i} + \sum_{i=1}^{e} \beta_{10} GN_{t-i} + \varepsilon_t \quad (6)$$

where Δ denotes first difference, ε_t is the error term, and a-e is the max lag instructions specified by the AIC. The F-statistic examines whether linear indices have a long-term equilibrium relationship. The ARDL model also assesses the interactions between the variables over the long and short term. The long-term relationship is measured using the ARDL model, which is as follows:

$$\Delta CO2_t = \gamma_0 \sum_{i=1}^{p1} \gamma_1 CO2_{t-i} + \sum_{i=0}^{p2} \gamma_2 RET_{t-i} + \sum_{i=0}^{p3} \gamma_3 EI_{t-i} + \sum_{i=0}^{p4} \gamma_4 EPU_{t-i} + \sum_{i=0}^{P5} \gamma_5 GN_{t-1} + \varepsilon_t \quad (7)$$

To estimate the short-run association for the specified model, the ARDL-ECM model could be used as follows:

$$\Delta CO2_t = \gamma_0 \sum_{i=1}^{p1} \gamma_1 CO2_{t-i} + \sum_{i=0}^{p2} \gamma_2 RET_{t-i} + \sum_{i=0}^{p3} \gamma_3 EI_{t-i} + \sum_{i=0}^{p4} \gamma_4 EPU_{t-i} + \sum_{i=0}^{P5} \gamma_5 GN_{t-1} + \gamma_6 ECM_{t-1} \mu_t \quad (8)$$

3.5. Gradual shift causal

The model developed by Toda and Yamamoto (1995) is premised on the vector autoregressive (VAR) model described by Sims (1980). When determining the best lag length, $\rho + d_{\max}$ is appended to the lag of $\rho + d_{\max}$ (the maximum integrated order of the time series). As a result, the VAR model's outcome is suspect (Enders & Jones, 2016; Enders & Lee, 2012). Therefore, Nazlioglu et al. (2016) expanded the Fourier Toda - Yamamoto causality test into five distinct frameworks to capture structural changes in the Granger causality analysis and add smooth shifts. The Fourier Granger causality test was lately created, employing a single frequency (SF) and cumulative frequencies (CF), respectively, and is known as the Fourier approach (Nazlioglu et al., 2019). The redesigned Wald test statistic combines the TY-VAR evaluation with the Fourier estimation (MWALT). Considering the intercept coefficients are constant across time, the VAR model is modified into Eq. (6) as specified:

$$y_t = \sigma\ (t) + \beta_1 y_{t-1} + \ldots + \beta_{\rho+d} y_{t-(\rho+dmax)} + \varepsilon_t \quad (6)$$

Where y_t signify CO_2, RET, EI, EPU and GN, while intercept, coefficient, error term and time symbolise by σ, β, ε *and* t respectively. Subsequently, in Eq. (7), the Fourier Toda Yamamoto causality with single frequencies is expressed as:

$$y_t = \sigma_0 + \gamma_1 \sin\left(\frac{2_{\pi} kt}{T}\right) + \gamma_2 \cos\left(\frac{2_{\pi} kt}{T}\right) + \beta_1 y_{t-1} + \ldots + \beta_{\rho+d} y_{t-(\rho+d)} + \varepsilon_t \quad (7)$$

In this case, the H0 for non-causality is tested (H0: ß1 = ß0 = 0), and the Wald statistic is employed to confirm the hypothesis. We also use the CUSUM and CUSUMQs diagnostic inspection to evaluate the model robustness. To validate the serial correlation, the Breusch Godfrey LM test is utilised. To detect heteroscedasticity, the BG test is performed. The JB test is also used to determine residual normality ARCH. Finally, the Ramsey-reset test was used to specify the model.

Table 2. Descriptive summary.

Statistics	CO_2	RET	EI	EPU	GN
Mean	15.485	0.077	2.350	4.655	4.349
Median	15.477	0.067	2.341	4.695	4.358
Maximum	15.572	0.123	2.662	5.149	4.415
Minimum	15.388	0.047	1.915	4.267	4.237
Std. Dev.	0.056	0.026	0.189	0.250	0.054
Skewness	0.039	0.552	−0.084	0.176	−0.719
Kurtosis	1.851	1.807	2.281	2.205	2.327
Jarque–Bera	1.657	3.301	0.682	0.944	3.150
Probability	0.437	0.192	0.711	0.624	0.207

Source: Author's own estimation.

Table 3. Unit root analysis.

	Constant, Linear Trend		LS (2013) Break in level			
Variables	ADF at Level	PP at Level	LM statistic	BD	lag	Sig. Level (CV)
CO_2	0.880	0.875	-4.90^a	2012	8	1% (−3.65)
RET	0.647	0.739	−1.74	2001	7	5% (−2.69)
EI	0.690	0.713	-3.97^a	2001	7	10% (−2.34)
EPU	0.099^c	0.315	-3.73^a	2007	5	
GN	0.519	0.882	−1.95	2006	6	
ADF and PP at 1st difference			LS (2013) Break in level & trend			
CO_2	0.004^b	0.004^a	-6.43^b	2007	8	1% (−6.60)
RET	0.000^a	0.000^a	-4.82^a	2004	1	5% (−5.07)
EI	0.000^a	0.000^a	-4.18^c	2008	7	10% (−4.36)
EPU	0.021^b	0.023^b	-4.77^b	2008	5	
GN	0.034^b	0.000^a	-5.27^b	2008	8	

Notes: **(a, b, c)** signifies the 1%, 5% and 10%. While BD represents the break date.
Source: Author's own estimation.

4. Results and discussion

Descriptive statistics such as mean, median, standard deviation, minimum, maximum, skewness, and Kurtosis are summarised in Table 2. The Kurtosis findings suggested that the data were normally distributed. To conclude the quantitative information, it also shows the highest by Kurtosis; JB estimations indicate a normal tendency, and the average CO_2 emissions are 15.485 higher than other variables. The outcome shows an upward trend in RET, EI, EPU, and GN. In addition, the variable trend graph is shown in Appendix Figure A1.

Table 3 shows the stationarity of each variable using ADF, PP, and LS 2013. The calculated findings show that the series under investigation is not stationary at I.(2). The ADF findings demonstrate that EPU is significant at the level, and further data from ADF and PP indicate that all variables are significant at the first difference. There is no notable series at I (2).

In addition, the next study used the LS 2013-unit root test in Table 3. The results demonstrate that CO_2, EI, and EPU are significant at the break-in level, with break years 2012, 2001, and 2007, respectively. While all factors show substantial at the Break in level and trend. Whereas 2007, 2004, and 2008 show signs of one structural break. Specified years in Pakistan saw structural disruptions due to various factors, including slow economic progress caused by political turmoil and exceptionally low oil prices in the wake of the Asian financial crises. Political upheaval and oil strikes in 2002-2003 compounded the economy's downfall (Zhang et al., 2022). However,

Table 4. Augmented ARDL bounds test.

Model	$F_{overall}$		t_{DV}		F_{IDV}	
$CO_2 = f(RET + EI + EPU + GN)$	5.908[a]		−3.729[a]		6.603[b]	
	Pesaran et al. (2001)				Sam et al. (2019)	
Critical Values (CV)	$F_{overall}$		t_{DV}		F_{IDV}	
Significance	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
10%	2.45	3.52	−2.57	−3.66	2.22	3.84
5%	2.86	4.01	−2.86	−3.99	2.8	4.7
1%	3.74	5.06	−3.43	−4.6	4.15	6.83

Source: Author's own estimation.

Table 5. Augmented ARDL short and long-run analysis.

Short-run variables	Coeff.	Std error	t-value
ΔRET	−2.894	1.119	2.412[b]
ΔEI	−0.109	0.064	−1.709
ΔEPU	−0.057	0.022	−2.410[b]
ΔGN	1.215	0.667	1.822[c]
ECM (−1)	−0.786	0.249	−3.081[a]
Long-run variables			
RET	−1.727	0.663	−2.604[b]
EI	−0.154	0.046	−3.340[b]
EPU	−0.069	0.021	−2.841[b]
GN	1.315	0.267	4.917[a]

Note: ([a]), ([b]) and ([c]) are significant at 10%,5% and 1%, respectively.
Source: Author's own estimation.

after the strikes, the economy continues to grow at a higher rate between 2004 and 2008. The findings verify that the ARDL model can be employed with the orders I(0) and I(I).

The bounds test is performed to examine the long-term link between the factors. The augmented ARDL bound test results and the critical values (CV) applied to establish the significance of the obtained test statistics are summarised in Table 4. These CV calculated using Pesaran et al. (2001) for the F-general and t-tests, Narayan for the general F-test adjusted for a small sample size, and Sam et al. (2019) for the F-test for explanatory factors. At all three tests, the augmented ARDL cointegration findings surpass the CV in the lower and upper bounds at the 1% and 5% significance levels. Consequently, the series are cointegrated and evolving in lockstep over time.

Table 5 displays the empirical evidence for the short and long term. Renewable energy transition has a detrimental impact on CO_2 emissions in the short and long term of 2.894 and 1.727. This implies that the energy transition process may help to reduce environmental damage in the United States. One probable explanation for the strong negative impact of RET on carbon emissions is the rising trend of investment in renewable energy in the United States. According to Bloomberg, private investment in U.S. clean-energy assets hit a record $105 billion last year, as the nation installed an unbelievable generating capacity. Based on an annual report by Bloomberg and the Business Council for Renewable Energy, the investment inflow is 11% greater than in 2020 and indicates a 70% increase over the previous five years. Private investment in US assets such as wind farms and solar plants accounts for around 14% of the $755 billion worldwide private investment committed last year (Eckhouse, 2022). Many governments, corporations, and climate-conscious investors are working to create green power systems and reduce emissions. In accordance with the research

"2022 Sustainable Energy in America Factbook," $47 billion of last year's private investment in the United States went into renewable energy, and $35 billion went toward electric transportation. The outcome aligns with Abbasi et al. (2021a) that renewable energy has a detrimental and statistically significant influence on environmental deterioration in Thailand. Koengkan and Alberto Fuinhas (2020) highlighted that energy transition can enable LAC nations to reduce environmental deterioration.

On the other hand, the EI coefficient is negatively associated with environmental vulnerability and positively impacts environmental cleanliness. Furthermore, the findings indicate that a 1% increase in EI substantially influences cutting carbon emissions by 0.154 in the long term. This suggests that reducing CO_2 emissions in the US economy positively influences environmental sustainability. According to findings, all pollution-control strategies (deterrence of problematic substance release), sewage treatment (managing, therapeutic interventions, and removal of waste), green tech (progress in manufacturing techniques), and clean tech (mitigation technology) have a beneficial effect on the environment efficiency (Sun et al., 2021; Wahab et al., 2020; Zheng et al., 2022). Additionally, the government and industry are focusing more on R&D that develops environmentally friendly capital items and boosting the efficiency of industrial technology that preserves low energy (Ali et al., 2022; Ali et al., 2020). The current study's empirical findings are in line with the preceding literature. For example, Ji et al. (2020) demonstrated that eco-innovation avoids environmental deterioration in a sample of fiscally decentralised economies. In contrast to Chunling et al. (2021) results, the conclusion indicated that ecological advancement boosts the environmental burden.

Furthermore, the effect of economic policy uncertainty is significant at the 5% level. Although the EPU has a negative coefficient, it is statistically meaningful. Imply that a 1% rise in EPU reduces emissions by 0.057 and 0.069% in the short and long-run, respectively. The short- and long-run statistics show that a positive change in EPU reduces emissions. As a result, lowering EPU is extremely desired to achieve a significant long-term decrease in CO_2 emissions. This fact might be connected to the notion that EPU could have a detrimental impact on economic circumstances, which can impact total company activity, lowering energy usage and CO_2 emissions (Jiang et al., 2019). The outcome similar to Ahmed et al. (2021), Danish et al. (2020b) indicated a positive change in EPU reduced emissions by 0.0256% in the US. In contrast to Wang et al. (2020) results, EPU is positively related to CO_2 emissions in the long term in the United States. The explanation for this might be because EPU is assessed as a world uncertainty index. This conclusion is fair since reducing economic policy uncertainty is critical for environmental policy consistency. Furthermore, during periods of lower economic uncertainty, companies can access cleaner energy sources rather than low-cost fossil fuels, and the government may concentrate on environmental stewardship problems. As a result, it is preferable to lessen EPU to maintain a sustainable reduction in CO_2 emissions.

Additionally, the globalization outcome has a favourable and statistically significant association with CO_2 emissions. As globalization quickens by 1%, CO_2 emissions rise between 1.215 and 1.315 percent in the short- and long-term. The findings are consistent with those of Abbasi et al. (2021a), Usman et al. (2020a) and Usman et al.

Table 6. Diagnostic inspection.

Diagnostic test	Hypothesis	P-value	Decision
Breusch-Godfrey LM	H_0: No serial correlation	0.826	≠
Breusch-Pagan-Godfrey	H_0: Homoskedasticity	0.959	≠
Jarque-Bera test	H_0: Residuals are normally distributed	0.389	≠
Ramsey RESET test	H_0: Model applied correctly	0.902	≠

Note: ≠ denotes H0 rejected.
Source: Author's own estimation.

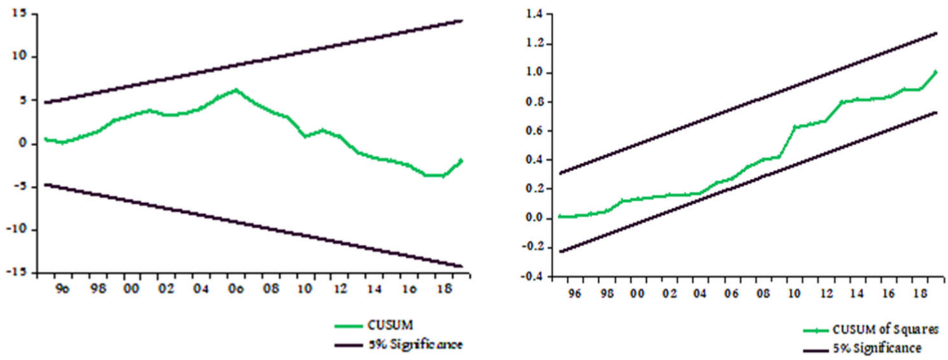

Figure 3. CUSUM and CUSUM SQUARE.
Source: Author's own estimation.

(2020b), who discovered that globalization had a positive influence on environmental deterioration in the United States and South Africa. While the results contrast with those of Zaidi et al. (2019) concluded that globalization considerably reduces carbon emissions in APEC nations. This finding suggests that the country's carbon emissions increase as global interconnection speeds up, degrading the environment. However, the Error Correction Model (ECM) findings show that the ECM is −0.786, implying that CO_2 emissions in the United States converge to the long-run equilibrium point at a 79% annual rate of adjustment.

4.1. Diagnostic examination

Several diagnostic approaches validated the appropriate model, as shown in Table 6, and proved the absence of serial correlation and heteroscedasticity. The Jarque-Bera and Ramsey RESET tests likewise excluded the H0, indicating that the estimated residuals are normally distributed, and the model is adequately parameterised. In other words, the model is accurate for policy purposes.

Finally, we use the structural stability assessment of the models to validate their robustness, as well as the cumulative sum of recursive residuals (CUSUM) and cumulative sum of recursive residual squares (CUSUMSQ) proposed by Pesaran and Pesaran (1997). Figure 3 illustrates graphic representations of CUSUM and CUSUMSQ, respectively. According to the standard, model parameters are stable over time if plots remain under a key limit of 5%. According to our model trend, CUSUM and CUSUMSQ are inside the bounds at a 5% level.

Further, following Bandyopadhyay et al. (2022) and Zhang et al. (2022), the study employed a novel gradual shift causality test developed by Nazlioglu et al. (2019).

Table 7. Gradual shift causality test.

Direction of causality	Wald	P-value	Frequency	Decision
RET $\rightarrow CO_2$	16.906	0.031[b]	1	Unidirectional
$CO_2 \neq$ RET	3.715	0.882		
EI $\neq CO_2$	6.383	0.604	1	no-causality
$CO_2 \neq$ EI	1.328	0.995		
EPU $\rightarrow CO_2$	47.508	0.000[a]	1	Bi-directional
$CO_2 \rightarrow$ EPU	16.833	0.032[b]		
GN $\rightarrow CO_2$	18.638	0.017[b]	1	Unidirectional
$CO_2 \neq$ GN	8.886	0.352		

Notes: (**a, b, c**) imply 10%, 5%, and 1%.
Source: Author's own estimation.

The outcome report in Table 7 reveals that RET- CO_2 and GN- CO_2 have a unidirectional causality. Whereas EI- CO_2 shows no causal relationship also, EPU- CO_2 indicates a bidirectional causal association. The outcomes are consistent with Cherni and Essaber Jouini (2017), Jiang et al. (2019), Pirgaip and Dinçergök (2020), Rahman and Vu (2020), and Usman et al. (2020b). As a consequence of the empirical findings of this research, we recommend that policymakers and government officials boost measures that encourage successful renewable energy measures. It would reduce environmental deterioration severity, boost production, and maintain a sustainable environment. More importantly, the magnitude of renewable energy consumption indicates that the United States economy is on the correct road toward decarbonization and sustainable development. Nonetheless, the US government and energy regulators must take active actions to expand energy sources to reduce fossil fuels and increase the use of low-carbon technologies. As per EIA (2018), petroleum is estimated to account for 36% of total energy consumption in the United States, with natural gas accounting for 31%, coal accounting for 14%, and renewable and nuclear electric power sources accounting for 11% and 8%, respectively (Usman et al., 2020b).

5. Conclusion and policy recommendations

Despite many empirical studies and different policies adopted at international forums, environmental pollution tends to rise globally. In an ever-changing world, it is still necessary to analyse the influence of different macroeconomic variables on environmental deterioration. To that goal, this research aims to establish the dynamic relationships between renewable energy transition, ecological innovation, economic policy uncertainty, and globalization considering data from 1990 to 2019 for the United States. We employed an augmented ARDL model, a robust statistical method developed lately by McNown et al. (2018) and Sam et al. (2019), to validate the long-run link between the variables. Also, the study used a gradual shift causality test recently established by Nazlioglu et al. (2019). The outcome reveals that renewable energy transition and economic policy uncertainty decreases carbon emissions in the long and short run, while ecological innovation reduces CO_2 emissions in the long run. Besides that, globalization rises carbon emissions in the long and short-run. The outcomes of the causality test show that renewable transition and globalization have unidirectional causation, but economic policy uncertainty has bi-directional causality. However, no causality evidence was identified between ecological innovation and carbon emissions in the United States.

5.1. Policy recommendations

a. The government should use several policy actions to improve environmental health. The study's outcomes provide a few fascinating policy views on environmental sustainability. The empirical evidence indicates that the growing trend in environmental quality in the United States is inefficient. This might be because the US economy is primarily dependent on fossil-fuel-based energy. According to the latest current BP statistics, the US is the world's second-highest producer of greenhouse gases. The US economy must prioritise the shift to renewable energy. We may design policy solutions based on empirical findings by examining them.

b. The American economy can build many initiatives based on the concept of green growth. To fulfil rising energy demand, the US government must invest in renewable energy projects, accelerating green growth. The government should encourage diverse companies to employ clean production processes, and incentives should be provided to firms that use green energy practices. Furthermore, the government should launch a nationwide awareness program to motivate people to live less resource-intensive lives. The usage of mass and social media may aid in achieving the intended result. Moreover, it is a necessary step to modify the national school curriculum. It is critical to discuss several themes relating to the environmental effects of using renewable energy. This step will start a household-wide awareness campaign.

c. Another major conclusion from our research is the significance of ecological -innovation in improving the sustainability of the environment. Policymakers must design policies that encourage investment in environmentally friendly technology. Furthermore, the government should begin new initiatives and stimulate R&D in ecologically friendly technology. In this context, the US should launch new programs in collaboration with the business sector. Moreover, to solve environmental degradation, it is necessary to encourage new and diversified renewable energy sources at the household and commercial levels.

d. Further empirical evidence suggests that economic policy uncertainty contributes to the deterioration of CO_2 emissions. In terms of practical implications, economic policy is a substantial resource for government jurisdiction and regulation. We encourage the government to guarantee consistency in policies connected to economic and environmental condition improvement. Economic policy changes will aid in the transition to renewable energy for businesses, homes, and other significant sectors that may contribute to pollution reduction. Undoubtedly, the United States has a modern economy with the resources necessary to transition to greener growth and decarbonization strategies. It is crucial to note that, especially in developed countries, internal and external markets are also affected by economic uncertainty. However, precautions should be taken to decrease policy-related economic uncertainty and assist in diminishing environmental deterioration, which is a primary aim of the United States to achieve the 2030 Sustainable Development Goals.

e. Besides, globalization increases the pressure on carbon emissions; it is recommended that, even though it is speeding up the US economy, strict environmental regulations should be imposed to counteract globalization's environmental degradation effect. The United States must cooperate more with its trading partners on a regional and global scale to further globalization and promote long-term prosperity. This may be accomplished by reducing trade obstacles. Additionally, since environmental sustainability is a prerequisite for globalization, initiatives must be made to enhance environmental quality.

5.2. Study limitation and future direction

There are limits intrinsic to this form of the model, and this study is not immune to them. Due to data limits, the simulation does not evaluate the potential advantages of Reducing emissions, which needs more investigation. The methodology offered here may be used to research various areas and generate a unique intellectual viewpoint.

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Appendix A

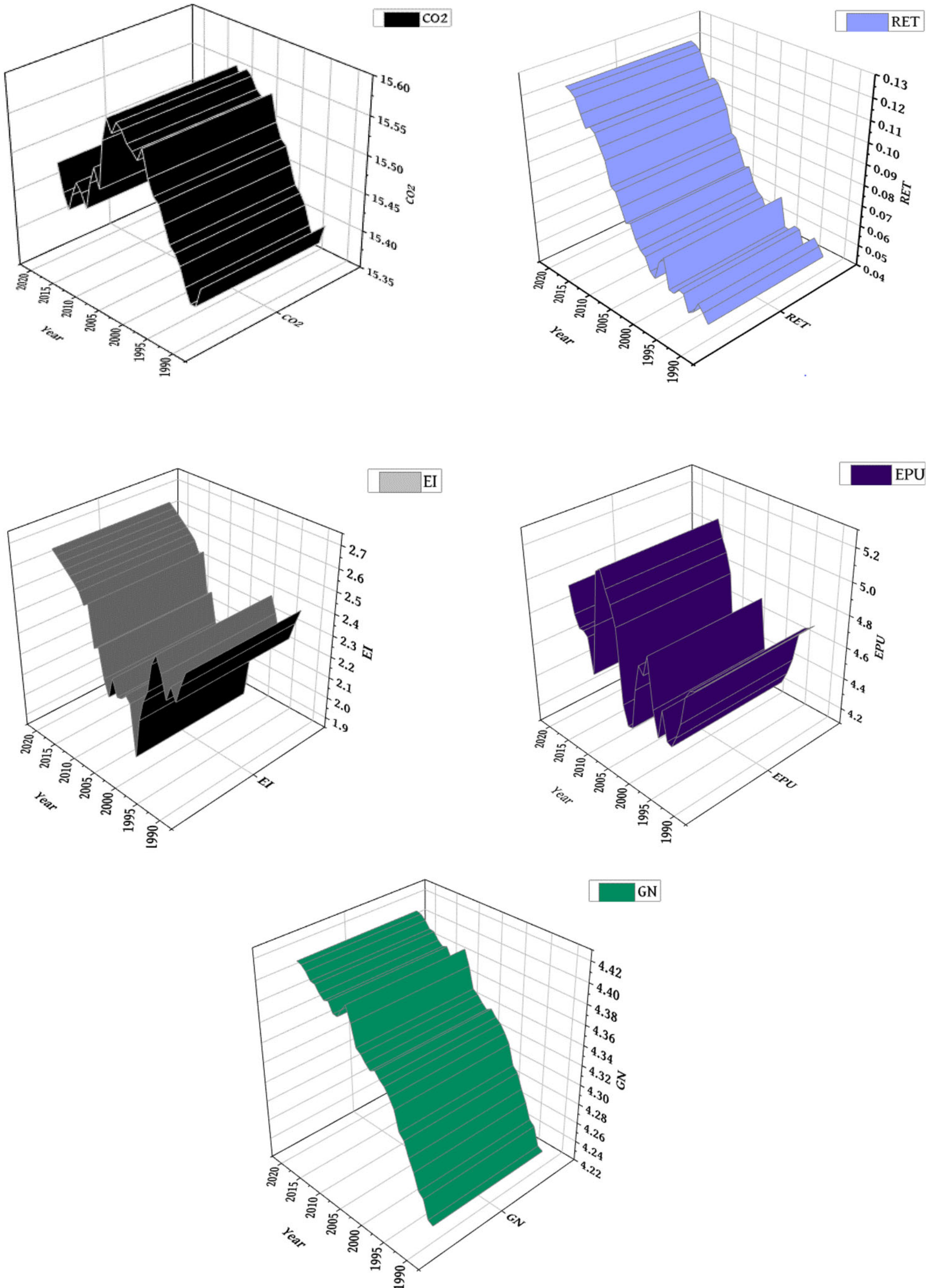

Figure A1. Data series and trend.
Source: Author's own estimation.