The Impact of Adult Awareness of Climate Change on Renewable Energy Consumption in the United States

Mohammad Ismayl Al Masud *

Abstract

I conduct a survey among college students in Texas to assess their willingness to pay for renewable energy to tackle climate change. An individual with a good level of climate awareness is 9.38% more willing to pay extra for renewable energy. Comparably, people with an excellent level of awareness are 23% more likely to financially favor renewable energy than others, given the willingness to pay those with a good level of awareness. At least 70% of survey participants want to pay at least $0.50, and 26% are willing to pay $1.50 more per gallon of gasoline to slow down climate change. Utilizing the autoregressive distributed lag (ARDL) model, I analyze the national-level data to extrapolate the individual-level results on a macroeconomic level. I find that a 1% increase in awareness level would cause an increase in REC by 0.32%, but a $1 increase in the oil price would lead to a rise in REC only by 0.002%. The environmental stringency index (EER), newspaper coverage of climate change (NC), and education (CG) all have statistically significant effects on REC. However, the renewable energy investment (RI), Palmer drought severity index (PDSI), and climate extreme index (CE) have no substantial impact on REC. Finally, I utilize the Global Trade Analysis Project (GTAP) to assess the economic and environmental consequences of increased renewable energy consumption driven by a demand shock.

Keywords: Climate change, Awareness, Renewable Energy, Endogeneity.

JEL Classification: Q20 , Q54

1 Introduction

Climate awareness [1] and renewable energy consumption represents a critical nexus in the contemporary landscape of environmental sustainability and energy transition. This paper delves into the interplay between individual awareness of climate change and the adoption of renewable energy sources. In this study, at the individual level, I find a strong willingness among people to financially support renewable energy when they possess a higher awareness of climate change. An individual with a good level of climate awareness is 9.38% more willing to pay extra for renewable energy. Comparably, people with an excellent level of awareness are 23% more likely to financially favor renewable energy than others,

*Department of Economics, Texas Tech University. Email: Mohammad-ismayl.masud@ttu.edu

[1] In the 1970s, pioneering works, such as Jeske (1978), underscored the significance of awareness for both societal organizations and individuals. Environmental awareness emerged as a nascent discipline during this period, encapsulating the emotional facet of environmental apprehension cultivated through early exposure to the natural environment. This emotional connection aligns closely with the concept of "sensitivity," as expounded by Tanner (1980), Chawla (1998), Hungerford and Volk (1990)

given the willingness to pay those with a good level of awareness. Consequently, it is reasonable to anticipate high climate awareness should lead to more renewable energy consumption and a greater degree of interchangeability between fossil fuels and renewable energy sources. But at the macro level, I find that a $1 increase in the average oil price corresponds to a mere 0.002% increase in renewable energy consumption. The inclination of high awareness toward a higher willingness to consume renewable energy is not reflected in the broader macro data.

The interplay between environmental awareness and renewable energy adoption is a multifaceted puzzle that remains significantly unresolved despite gaining attention since the 1980s. The limited uptake of renewable energy sources can potentially be attributed to three hypotheses: either a deficiency in environmental awareness leading to low renewable energy consumption or a lack of public concern about climate change resulting in low consumption of renewable energy, or people are aware of climate change, but there are technological and structural constraints to adopting renewable energy sources. These hypotheses, though tantalizing, have thus far eluded empirical scrutiny within the existing body of literature. To bridge this gap in our understanding, this study embarks on a mission to tether the first hypothesis, focused on environmental awareness, to concrete outcomes in terms of renewable energy consumption, both at the micro and macro levels.

So, the hypothesis states that if there is high awareness, renewable energy adoption should be high as well. However, it doesn't reflect in macro data since I find a very low degree of interchangeability between oil pricing and renewable energy prices. That must mean there is not enough climate awareness, and the crucial question arises, how is my awareness being improved by a policy measure? I focus on newspapers as a potential awareness-building mechanism. The newspapers, as a formidable influencer on public opinion, possess the potential to either bolster or hinder the adoption [2] of renewable energy sources. Utilizing autoregressive distributed lag modeling to derive causality, I find that for every 1% increment in the overall volume of climate change articles in prominent newspapers [3], there is a corresponding 4.63% decrease in renewable energy usage. This media influence can potentially be multifaceted. First, when the media disproportionately emphasizes negative aspects of renewable energy, such as intermittent power generation or high initial costs, it can inadvertently discourage public support and investment. Second, sensationalized depictions of climate change can engender a sense of futility, leading individuals to question the efficacy of individual actions, including the adoption of renewable energy. Lastly, biased reporting or the amplification of climate change denial can kindle skepticism surrounding the urgency of transitioning to renewable energy sources, ultimately impeding the necessary policy changes and societal commitment essential for widespread adoption.

[2] Positive coverage can raise awareness, elicit support for renewable energy, stimulate investments, and evoke policy advocacy. Conversely, negative or biased media portrayals, such as climate change denial or the accentuation of renewable energy challenges, may act as a deterrent to investment and public support.

[3] Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal

Also, education may act as a catalyst for building awareness and increasing renewable energy consumption by equipping individuals with the knowledge, skills, and motivation to support and adopt sustainable practices. It also contributes to a broader societal shift toward a greener and more environmentally conscious future. This study finds that a 1% increase in the number of college graduates corresponds to a 0.002% increase in renewable energy consumption. College graduates, as a cohort, tend to exhibit heightened environmental consciousness and, therefore, can contribute to the long-term transition towards cleaner energy sources. Their proclivity for advocacy and education can kindle shifts in societal norms and foster a culture of sustainability. The cumulative effect of their efforts may not be immediate, but it significantly contributes to the trajectory of increased renewable energy adoption and reduced carbon emissions over the long term.

The context of this study emerges against the backdrop of environmental awareness, shifting energy demands, and regulatory paradigms that seek to mitigate the profound impact of climate change. A pivotal driver of climate change is the extensive reliance on fossil fuels, particularly coal, crude oil, and natural gas, which has emerged as the dominant energy source owing to cost advantages over renewables such as hydropower, solar energy, and wood energy. Nonetheless, the economic consequences of fossil fuel dependence extend far beyond the apparent cost considerations. Consumers bear the direct expense of fossil fuels while simultaneously shouldering the substantial negative externalities of damaging the climate, an aspect thoroughly explored in research by Caretta, Arfanuzzaman, Morgan, Kumar, et al. (2022), Park, Behrer, and Goodman (2021), Isen, Rossin-Slater, and Walker (2017), Carleton and Hsiang (2016), Graff Zivin and Neidell (2013).

The ramifications of climate change are immense and multifaceted (Caretta et al. (2022), Park et al. (2021), Isen et al. (2017), Carleton and Hsiang (2016), Graff Zivin and Neidell (2013)), with potential economic impacts projected to reach up to 20% of the world's gross domestic product (GDP) within a generation (Nordhaus (2007)). Additionally, the looming threat of global temperatures rising by an alarming 36.86 degrees Fahrenheit in the next century, significantly surpassing the current target of 34.7 degrees Fahrenheit, as noted in the latest climate change tracking data (Tracker (2022)), underscores the urgency of averting a climate catastrophe. To meaningfully alter emissions trajectories, both individual behavioral changes and comprehensive shifts in government policy are deemed indispensable.

A compelling solution to address the unfolding environmental crisis is the transition from fossil fuels to renewable energy sources. The shift towards increased renewable energy utilization promises manifold benefits, from bolstering the gross domestic product (Dogan, Altinoz, Madaleno, and Taskin (2020), Zafar, Shahbaz, Hou, and Sinha (2019), Atems and Hotaling (2018), Wang, Wang, Ma, and Gong (2011)) to decelerating environmental degradation and remediating existing environmental harms (Alvarado et al. (2019)). A large part of the U.S. population acknowledges global warming (Ballew et al. (2019), Bergquist and Warshaw (2019),Bord, O'connor, and Fisher (2000), Krosnick, Holbrook, and Visser (2000),Shwom et al. (2015), Hamilton and Keim (2009), Schuldt, Konrath, and Schwarz (2011), Shao (2017)), however, a conspicuous void persists in our understanding of how environmental consciousness among U.S. adults intersects with renewable energy consumption.

To unravel this relationship, I employ a mix of micro and macro approaches. Firstly, I conduct a survey among Texas college students to gauge their awareness levels of climate change and willingness to pay for renewable energy. The results underscore a compelling linkage: students with heightened awareness levels of climate change are 23% more inclined to pay a premium for renewable energy. Additionally, I find that at least 80% of students are aware of environmental issues and renewable energy, 87% believe the state should educate citizens about climate change, renewable energy, and environmental protection, and around 50% of them want to pay at least $0.20 per gallon more for gasoline. Building upon these individual-level insights, I extrapolate the findings to a macroeconomic context using national-level data.

Utilizing autoregressive distributed lag modeling, I form a macroeconomic analysis and find the dynamics between awareness and renewable energy consumption. My analysis reveals that a 1% increase in awareness level corresponds to an increase in renewable energy consumption by 0.32%. I adopt the total number of Google searches on climate change as a proxy for climate awareness to trace the short- and long-term causalities between renewable energy consumption and climate awareness.

Considering that renewable energy stands as one of the primary alternatives to fossil fuels, the price of fossil fuels emerges as a critical factor in the decision-making processes related to energy. I find a $1 increase in crude oil price, on average, leads to a 0.002% increase in renewable energy adoption. The rationale underpinning this relationship lies in the premise that surging oil prices render fossil fuels more expensive, prompting some consumers and industries to explore alternatives, including renewable energy (Moriarty and Honnery (2016), Dincer and Rosen (2004)). However, this transition involves substantial upfront costs, deterring immediate adoption due to economic uncertainties stemming from elevated oil prices despite the long-term cost savings and environmental benefits associated with renewable energy. In literature, the impact of oil price on the REC differs (see for example, Apergis and Payne (2010), (Bowden and Payne (2010), Sadorsky (2009), Omri and Nguyen (2014), Brini, Amara, and Jemmali (2017), Luqman, Ahmad, and Bakhsh (2019), Khan, Yasmeen, Shakoor, Khan, and Muhammad (2017)).

Finally, I explore the pivotal role of energy and environmental regulations in shaping renewable energy consumption. These regulations, as institutional frameworks, serve as essential drivers for the development and adoption of clean energy sources. Their potency is grounded in their ability to set renewable energy targets, offer financial incentives, and impose emissions limits, thereby stimulating investments by businesses and individuals. These regulations also level the playing field, rendering clean energy more competitive with traditional fossil fuels. My findings, however, underscore that the impact of regulations can be gradual. The implementation of regulatory changes is often mired in intricate legislative processes, leading to delays. Opposition from industry stakeholders, political resistance, budget constraints, and infrastructure development further contribute to the protracted regulatory impact. Additionally, the long-term nature of renewable energy projects, characterized by substantial upfront costs and extensive infrastructure development, implies that the effects of regulations may only manifest over an extended period. While regulations are incontrovertibly pivotal in driving renewable energy adoption, their effects can be incremental, underscoring the need for sustained commitment and perseverance.

In summation, this research spans multiple dimensions of renewable energy adoption, encompassing individual climate awareness, economic factors, media influence, education, and regulatory frameworks. By delineating the multifaceted landscape within which renewable energy consumption is embedded, we aspire to equip policymakers, researchers, and stakeholders with a comprehensive understanding of the intricate dynamics at play in the quest for a sustainable energy future.

The rest of the paper is structured as follows: Section 2 presents results and insights drawn from our survey. Then, in section 3, we test the survey results from the previous section with national-level data. Section 4 illustrates the diagnostic tests and results. Finally, Section 5 presents the conclusion and potential policy implications.

2 Micro Analysis

To measure individual-level perspectives on climate change and renewable energy, directly asking individuals about their opinions on climate change and renewable energy is probably the most efficient approach. For this study, I entirely question only college students due to budget constraints. For this study, I surveyed 406 students from Texas Tech University, Texas A&M University-Corpus Christi, and the University of Texas Rio Grande Valley.

Table 1 displays the summary statistics for the entire sample. The respondent's gender ratio is nearly equal (male 54%, female 45%). The respondents are 20 years old on average, and the majority of their parents—either the mother or the father—have a college degree. 69% of the participants, on average, were raised in a small city or rural location. The majority of participants (96.85%) are single, and 98.95% are permanent residents of Texas. Nearly equal numbers of participants are drawn from each college year.

Due to the dichotomous nature of our dependent variable, I adopt a logit model as a prediction model. Since the error terms are not required to have a normal distribution, linear regression would not be appropriate because the response values are not expressed as ratios (Hosmer, Lemeshow, and Sturdivant (2000)).

A logistic regression model allows one to calculate the probabilities that the modelled value will occur based on the values of the explanatory variables (Lučkaničová, Ondrušeková, and Rešovsky (2012)). The willingness to pay more for renewable energy is the dependent variable (log of the odds ratio) regressed against explanatory variables in our model. Therefore, I use a logit model to calculate the likelihood that someone would be in favor of paying extra for renewable energy given the specified variable: knowledge of climate change, whether or not they resided in a rural location, their age, gender, and the degree of education of their parents.

Table 1 Summary Statistics.

Characteristics		Mean (%)
Gender		
	Female	44.88%
	Male	54.48%
	Other	0.44%
Permanent Residence		
	Texas	98.95%
	Other	1.05%
College Year		
	Freshman	27.29%
	Sophomore	38.85%
	Junior	25.98%
	Senior	9.97%
	Graduate	0.79%
GPA		
	1.00-1.99	1.83%
	2.00-2.99	19.94%
	3.00-4.00	71.65%
Mothers' Education		
	University Degree	61.42%
	Diploma Degree	9.18%
	Other	30%
Fathers' Education		
	University Degree	52.76%
	Diploma Degree	10.76%
	Other	37%
Marital Status		
	Married	96.85%
	Single	6%
Hometown		
	Rural Area	10.76%
	Small City	58.72%
	Suburb	37.27%
	Large City	12.33%
Family Income		
	Under $50k	24.40%
	$50k-$100k	25.20%
	$100k-$150k	18.11%
	$150k-$200k	14.96%
	$200k+	19.94%
Mean Age (Years)		20.2
Number of Participants		381

We estimate the following logit model;

$$log(\frac{P_i}{1-P_i}) = \beta_0 + \beta_1 VGAL_i + \beta_2 GAL_i$$

$$+\beta_3 BG_i + \beta_4 Female_i + \beta_5 PE_i + \beta_6 RS_i + \beta_7 AGE_i + \mu_i$$

where,

P_i = probability that willing to pay more for renewable energy,

Very Good AL = 1 if the individual has a very good awareness level, 0 otherwise,

Good AL = 1 if the individual has a good awareness level, 0 otherwise,

Rural = 1 if the individual lived in a rural area, 0 otherwise,

Female = 1 if the individual is female, 0 otherwise,

Table 2 Logit Estimations of Climate Awareness on Renewable Energy Consumption.

Variables	(1)	(2)	(3)	(4)
Very Good AL	.9733** (.4517)	2.6461** (1.1946)	1.0469** (.4613)	1.2919*** (.4855)
Good AL	.4064* (.2289)	1.5016* (.3436)	.2330 (.2259)	.3373 (.2324)
Rural	.3992 (.3585)	1.4909 (.5342)	.3825 (.3516)	-.0141 (.3564)
Female	-.2981 (.2159)	.7422 (.1600)	-.0577 (.2135)	-.4844** (.2200)
Parent's Education	-.5811*** (.2195)	.5592*** (.1227)	-.3400 (.2162)	-.7777*** (.2247)
Marital Status	.0868 (.4487)	1.0889 (.4647)	.1859 (.4459)	.1202 (.4579)
Age	.0005 (.0481)	1.0005 (.04815)	-.0573 (.0483)	-.0640 (.0492)
Constant	.3007 (1.1869)	1.3508 (1.6033)	1.1121 (1.180)	1.9110 (1.2159)
Pseudo R2	0.0322	0.0322	0.0210	0.054

Note: The standard errors are in parenthesis and 10%, 5%, and 1% significant level are denoted by *, ***, *** respectively.

Parent's Education = 1 if the individual's father or mother has a college degree, 0 otherwise,

Relation Status = 1 if the individual is single, 0 otherwise,

AGE = the individual's age

From Table 2 (column 1), my logistic estimation suggests that students with a very good awareness of climate change are likelier to pay more for renewable energy than others. Additionally, students with a good awareness level are also more likely to pay more for renewable energy. However, students with one of their parents with a college degree are less likely to pay more for renewable energy. Parents' education and attitude can significantly influence their children's beliefs and behaviors, including their attitude toward climate issues. While parents with a college degree may generally be more educated and informed about environmental issues, their attitudes, and behaviors (like prioritizing economic concerns over environmental ones, lack of environmental awareness, and conservative attitudes) can inadvertently contribute to a negative impact on their kids' willingness to support renewable energy.

A person who grew up in a rural region may have developed a different perspective on environmental concerns than someone who lived in a city because they have a closer relationship with nature. However, we were unable to identify any statistically significant associations between such background and attitude towards the use of renewable energy in our study. Furthermore, gender, relationship status, and age are statistically insignificant in our estimation.

Table 3 Average Marginal Effects of Climate Awareness on Renewable Energy Consumption

Variables	(1)	(2)	(3)
Very Good AL	.2298** (.1041)	.2529** (.1086)	.2937*** (.1065)
Good AL	.0959* (.0531)	.0563 (.0543)	.0766 (.0522)
Rural	.0942 (.0841)	.0924 (.0844)	-.0032 (.0810)
Female	-.0703 (.0504)	-.0139 (.0515)	-.1101** (.0488)
Parent's Education	-.1372*** (.0499)	-.0821 (.0515)	-.1768*** (.0479)
Marital Status	.0205 (.1059)	.0449 (.1076)	.0273 (.1040)
Age	.0001 (.0113)	-.0138 (.0115)	-.0145 (.0110)

Note: The Delta-method standard errors are in parenthesis and 10%, 5%, and 1% significant level are denoted by *, ***, *** respectively.

Column 2 presents the estimation in odds ratio format. A unit increase in a very good awareness level will increase the odds of favoring renewable energy consumption by 2.67 units. Additionally, a unit increase in parents with a college degree decreases the odds of consuming renewable energy by 0.56 units. Additionally, to analyze a "representative student," for a single female student with one of the parents with a college degree or higher and who grew up in a rural area, a unit increase in very good awareness level is associated with a 0.236 increase in the probability of paying more for renewable energy. However, for a single male student with one of the parents with a college degree or higher but grew up in a rural area, a unit increase in good awareness level is associated with a 0.099 increase in the probability of paying more for renewable energy.

The outcomes of the same set of independent variables but two distinct dependent variables (willingness to pay to address climate change and reduce carbon emissions, respectively) are shown in columns 3 and 4. The close resemblance of the results to column 1 supports the consistency of the responses.

Furthermore, I estimate the marginal effects that are illustrated in Table 3 (column 1). From the results, a student with a very good awareness of climate change is 23% more likely to pay more for renewable energy.

Similarly, an individual with a good level of awareness is 9.38% more likely to favor financially renewable energy than others. Individuals' parents' education will likely negatively affect renewable energy by 12.49%. However, background, gender, relation status, and age are still statistically insignificant in our survey. Column 2 and 3 also presents very similar findings.

Fig. 1 Diagrams of Students Willingness to Pay to Reduce Climate Change

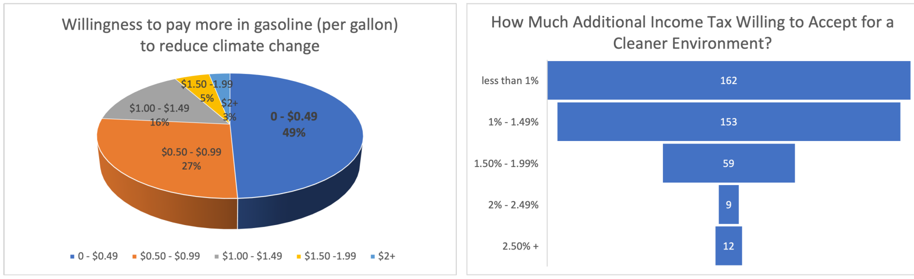
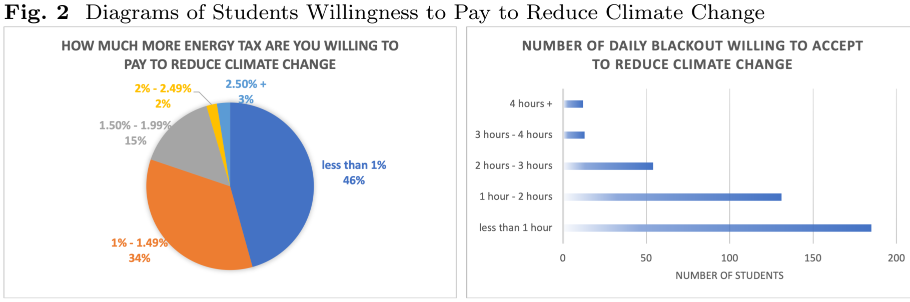


Fig. 2 Diagrams of Students Willingness to Pay to Reduce Climate Change



Additionally, I want to measure students' willingness to pay to reduce climate change in different forms of payment. In Figure 1, the pie chart asks how much more students are willing to pay per gallon of gasoline to reduce climate change, and at least 75% students are willing to pay less than a dollar more for gasoline. Around 20% of students are willing to pay more by $1.00 to $2.00. Given students usually live with quite a tight budget line, their willingness to pay to reduce climate change is very inspiring. The rest of the diagrams in Figure 1 and Figure 2 ask for different forms of payments to fight climate change, and the responses are very close to each other.

So, according to my survey results, I can assert that an agent with a good awareness of climate change is likelier to favor more to renewable energy consumption than others. I will test the assertion with macro data in the next section.

3 Macro Analysis

3.1 Data and Methodology

The data for this study were gathered on a consistent monthly basis between 2004 and 2020. Because time-series data are inherently stationary, and to test for stationarity, we applied the Augmented Dicky-Fuller (ADF) unit root test. I implement an autoregressive distributed lag (ARDL) model and an error correction model (EC) based on the Johansen cointegration technique to examine the long-run and short-run relationship.

Initially, I run an ADF test to determine whether the variables are stationary. The Johansen maximum eigenvalue and trace tests were adopted to investigate the existence of a cointegration after determining the variables' stationary level. I employ the ARDL models to establish the causality because our variables have both I(0) and I(1) level values.

3.2 Augmented Dickey-Fuller Unit Root Test

The mean and variance of economic and financial time series commonly exhibit non-stationarity, changing with time. Therefore, the first and necessary prerequisite for using time series techniques is that the variables be stationary. A variable with a finite mean and an autocorrelation that remains constant throughout time is considered to be covariance stable (Wooldridge (2015)). In short, when a series's mean, variance, and autocovariance remain constant across time, the series is said to be stationary.

I look at the stationarity properties to perform a cointegration study. A covariance-stationary process, often known as I (0), describes stationary variables at a level. If they remain stationary after taking their initial difference, they are referred to as I (1) processes or integrated at order 1 (Wooldridge (2015)). Therefore, when a variable becomes stationary at the q^th difference, it is in the integrated order of q, or I (q).

I must first check to see if all of the variables are stationary. The Phillps-Peron (PP, 1988) test, the Kwiatkowski, Phillips, Schmidt, Shin (KPSS, 1992) test, and the Augmented Dicky-Fuller (ADF, 1979) unit root test are the three most widely used tests for stationarity. Due to their varied constraints, choosing one or more tests from among them is frequently a challenge for researchers. For instance, the PP is condemned for having impoverished size parameters, whereas the ADF is frequently attacked for having poor power (Schwert, 1989). This study employs the ADF to determine whether the data are steady.

To identify a unit root in time series, the Augmented Dicky-Fuller test was proposed by Dickey and Fuller (Dickey and Fuller (1979) Said and Dickey (1984)) with mainly three possibilities. These three versions are as follows.

$$\Delta z = \rho z_{t-1} + \sum_{t=1}^{q-1} \rho_i z_{t-i} + \epsilon_t$$

$$\Delta z = \eta_0 + \eta_{1t} + \rho z_{t-1} + \sum_{t=1}^{q-1} \rho_i z_{t-i} + \epsilon_t$$

Where η_0 refers constant term, t refers time trend, ϵ_t is an error term, x_t is our variable at time t, and $\Delta z = z_t - z_{t-1}$. I aim to examine the following null and alternative hypotheses.

H_0: $\rho = 0$; Series carries a unit root

H_1: $\rho < 0$; Series is stationary.

3.3 Cointegration Test

Times series data tends to be extremely dynamic and non-stationary, which makes them susceptible to "spurious regression" cases. A group of variables can be non-stationary and have no real economic relationship, yet by regressing them, they may nevertheless show a statistically significant association.

This is referred to as spurious regression. However, the variables can be classified as cointegrated if they are not stationary, but a linear combination makes them so. The cointegration method finds any association between non-stationary time series data. Most financial and economic time series are non-stationary when seen separately, but when integrated linearly, they become stationary. Even if one of them deviates from equilibrium over time, the variable finally returns to its initial trend.

If both variables in a bivariate analysis are at I(1), the series will be cointegrated. But, following a linear combination, it will become I(0). Cointegration states that a collection of non-stationary time series with the same order (I(q)) shows the existence of a long-term relationship. Furthermore, the uniform stochastic trends shared by the cointegrated variables do not change over time. The presence of a cointegration relationship among the variables will improve the prediction of both the short-run and long-run relationship. Therefore, after confirming the integration order of the variables, we can do cointegration tests to see whether there is a cointegration relationship present in the model.

3.4 The Autoregressive Distributed Lag (ARDL) Model

To determine the long-term correlations between the variables of interest, many earlier studies used Johansen's (1988) co-integration and Engle-Granger causality approaches. This is due to the fact that several studies have established that this strategy is most accurate when the relevant variables are included in the same sequence. The 'Autoregressive Distributed Lag (ARDL)' bound test, a different co-integration method, was developed by Pesaran et al. (2001), Pesaran and Shin (1999), and Nayaran (2004). In comparison to the typical Engle-Granger two-step technique and Maximum Likelihood methods of cointegration, the ARDL model, commonly referred to as the "Bound Testing Approach", has several advantages (Johansen and Juselius (1990)).

Firstly, the more statistically significant approach to determining the co-integration connection in small samples is the ARDL model(Pesaran, Shin, and Smith (2001),Narayan (2004)). In contrast, accurate parameter estimation for Johansen co-integration approaches requires huge data samples. This shows that the approach overcomes the issue of biases caused by sample size.

The endogeneity problem is not present in the estimation. According to this strategy, Pesaran, Shin, and Smith (1999) claim that modeling ARDL with the appropriate number of lags will address issues with autocorrelation and endogeneity because different variables may have different optimal numbers of lags, whereas, in Johansen-type models, it is not possible for different variables to have different optimal lag lengths and instead all variables have the same lag length. Jalil and Ma (2008) also assert that the endogeneity issue is ignorable if the computed ARDL model does not suffer autocorrelation problems.

The third advantage of the ARDL method is its applicability regardless of whether the variables are integrated at a different level. This indicates that the ARDL technique does not have the pre-testing concerns associated with conventional cointegration, which calls for the variables to previously be classified as I(1), I(0), or a combination of both. (Pesaran et al. (2001)).

Furthermore, the simultaneous determination of model parameters for relevant variables is one of the additional advantages of bound testing in the long and short terms. Using the ARDL technique, we can derive estimators of the model that are objective and efficient (Narayan (2004), Pesaran et al. (1999)). In recent years, this method has become ubiquitous, appropriate for analyzing long-term relationships, and widely utilized in empirical research.

The specification of the ARDL model, in the long run, is the following:

$$log(REC)_t = \lambda_0 + \sum_{i=1}^{q} \lambda_1 log(REC)_{t-i} + \sum_{i=1}^{q} \lambda_2 log(AL)_{t-i} +$$

$$\sum_{i=1}^{q} \lambda_3 CE_{t-i} + \sum_{i=1}^{q} \lambda_4 EER_{t-i} + \sum_{i=1}^{q} \lambda_5 RI_{t-i} + \sum_{i=1}^{q} \lambda_6 log(NC)_{t-i} +$$

$$\sum_{i=1}^{q} \lambda_7 CP_{t-i} + \sum_{i=1}^{q} \lambda_8 CG_{t-i} + \sum_{i=1}^{q} \lambda_9 PDSI_{t-i} + \epsilon_t$$

The variables' long-run variation is represented by λ. Building an error correction model in the presence of cointegration makes it possible to infer the short-run elasticities. The error correction model used for the short-run ARDL model is as follows:

$$log(REC)_t = \lambda_0 + \sum_{i=1}^{q} \rho_1 \Delta log(REC)_{t-i} + \sum_{i=1}^{q} \rho_2 \Delta log(AL)_{t-i} +$$

$$\sum_{i=1}^{q} \rho_3 \Delta CE_{t-i} + \sum_{i=1}^{q} \rho_4 \Delta EER_{t-i} + \sum_{i=1}^{q} \rho_5 \Delta CP_{t-i} +$$

$$\sum_{i=1}^{q} \rho_6 \Delta RI_{t-i} + \sum_{i=1}^{q} \rho_7 \Delta log(NC)_{t-i} + \sum_{i=1}^{q} \rho_8 \Delta CG_{t-i} +$$

$$\sum_{i=1}^{q} \rho_9 t - i + \phi ECT_{i=1} + \epsilon_t$$

In the equation above, ρ represents the short-run variance, and ECT stands for the error correction term, which measures the rate of adjustment from disequilibrium. The error correction term's usual range is between 1 and 0. A statistically meaningful error correction term should be negative, indicating that any shock is adjusted to equilibrium in the following time period. According to Brown et al. (1975), CUSUM and CUSMSQ were used to test the stability of the model. The Breusch-Godfrey Lagrange Multiplier (LM) was employed to confirm the serial correlation. Breusch-Pagan-Godfrey (BG) and autoregressive conditional heteroscedasticity (ARCH) were employed to test for heteroscedasticity; Jarque Bera was used to test for residual normality. I validate my model specifications by using the Ramsey reset.

3.5 Granger Causality Test

One can look into the long-run and short-run causality between them once cointegration in the long-run relationship between renewable energy usage and awareness level has been verified using a bound test. The relationship between the REC and awareness level was investigated in both the long- and short-run using the vector error correction Granger causality paradigm. The following matrix serves as a model for the Granger causality paradigm.

$$(1-L)\begin{bmatrix} ln(REC)_t \\ ln(AL)_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \sum_{i=1}^{p} (1-L) \begin{bmatrix} \beta_{11} & \beta_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} ln(REC)_{t-i} \\ ln(AL)_{t-i} \end{bmatrix}$$
$$+ \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \begin{bmatrix} ln(REC)_{t-1} \\ ln(AL)_{t-1} \end{bmatrix} ECM_{t-1} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

Where the difference operator is (1-L), long-term causation is indicated by the coefficient for the latent error term. In contrast, short-run causation is indicated by the statistical significance of the F-statistic as assessed by the Wald test.

The substantial and negative coefficient of the lagged error term in the equation above suggests that the awareness level is the primary cause of long-term REC when renewable energy consumption is the dependent variable. The short-run causality link was determined using the Wald test. As a result, it can be said that awareness level is the short-run granger cause of the REC because the coefficients linked to the lagged values of the awareness level indicator are shown to be statistically significant.

Similar to the previous case, when awareness level is the dependent variable, the significant and negative coefficient of the latent error correction term suggests that the causal chain is not running from REC to awareness level.

3.6 Addressing Endogeneity

When running regressions, the potential for simultaneity between the REC and the right-side variables, particularly the awareness level, is a major concern (a topic stressed by Slemrod, Gale, and Easterly (1995)). According to various papers published in the middle of the 1990s, the estimates of the long-run parameter vector, B, from model OLS regressions are consistent in a broad range of situations (see, for example, Pesaran and Smith (1995); Pesaran et al. (1999)).

In addition to being able to identify the direction of the relationships between dependent and explanatory variables (i.e., avoiding the endogeneity problem), the ARDL technique can simultaneously estimate LR and SR coefficients. This method also eliminates the issues caused by autocorrelation and omitted variables. Therefore, since the ARDL technique's estimations for cointegration do not have serial correlation or endogeneity issues, they are precise and effective (Pesaran et al. (2001)).

Furthermore, the endogeneity problem is not present in the estimation. Pesaran et al. (1999) assert that it is conceivable for distinct variables to have various optimal numbers of lags in this technique; however, this is not allowed in Johansen-type models, and instead, all variables adopt the same lag length. Modeling ARDL with the proper number of lags would handle autocorrelation and endogeneity issues. Jalil and Ma (2008), if the ARDL estimations are autocorrelation-free, the endogeneity problem is impregnable.

Table 4 Unit Root Test

Variables	At Level	First Difference	Stationary Level
Log(REC)	-2.182	-16.631***	I(1)
Log(AL)	-4.655***	-15.058***	I(0)
CE	-5.317***	-5.258***	I(0)
EER	-12.267***	-8.377***	I(0)
RI	-3.539**	-5.654***	I(0)
CP	-2.666	-3.814***	I(1)
Log(NC)	-4.623***	-3.673**	I(0)
CG	-2.640	-5.320***	I(1)
PDSI	-2.835***	-2.984***	I(1)

Note: The standard errors are in parenthesis and 10%, 5%, and 1% significant level are denoted by *, ***, *** respectively.

Even if the bounds test technique to cointegration does not require pretesting for stationary of the model's variables, it is still crucial to do stationary tests on all of the series. The purpose of the unit root test is to ensure that the order of integration is not more than I(1), as this is the upper limit at which the ARDL limits test cannot be used to evaluate co-integration. Therefore, testing the series for stationary before performing any econometric analysis was essential. Notably, testing for unit roots is used to explore stationary features of time series. There are numerous ways to check for stationary. Thus, the regularly employed Augmented Dickey-Fuller (ADF) unit root test is applied in this work. Table 1 displays the results of the unit root testing.

3.7 Long-run ARDL Bounds Tests for Cointegration

The next step in the limits test approach of co-integration is estimating the ARDL model using the proper lag length selection criterion, as we have established that the variables are stationary. In other words, ARDL bounds analysis is performed to determine whether there are any long-run relationships between the model's included variables. The maximum lag length must be established before a cointegration test using the ARDL bound test can be conducted. This is because choosing the ideal lag length is a crucial issue addressed when using ARDL. The model was estimated using ARDL, and the best lag was chosen using the AIC technique (Akaike Information Criterion).

As seen from the results in Table 5, the F-statistic is 5.139, which is higher than the critical value for the upper bound at a 1% significance level. This unequivocally demonstrated a long-term link between REC and explanatory factors. As a result, the alternative hypothesis—that there is a long-term relationship between the variables—is accepted, and the null hypothesis—that there is no such relationship—is

Table 5 ARDL bounds test

Levels	*Bounds*	*Critical Values*
10%	Lower Bound I(0)	1.95
	Upper Bound I(1)	3.06
5%	Lower Bound I(0)	2.22
	Upper Bound I(1)	3.39
2.5%	Lower Bound I(0)	2.48
	Upper Bound I(1)	3.70
1%	Lower Bound I(0)	2.79
	Upper Bound I(1)	4.10
F-Statistics ARDL		**5.139**

rejected at the 1% significance level. In other words, the model's variables have a long-term relationship that serves as a foundation for assessing the explanatory variable's long-term impact on renewable energy consumption.

3.8 Long-run ARDL Estimation

All the variables in Table 6 show the predicted results except for news coverage of climate change. The awareness level, crude oil price, human capital, energy, and environmental regulation index statistically significantly influence the United States' use of renewable energy. However, the climate extreme index, investment in renewable energy, and the Palmer drought severity index are statistically insignificant in this study.

The ARDL output indicates the degree of climate change awareness has a long-term favorable impact on renewable energy consumption. At a 1% level of confidence, a 1% increase in awareness will cause the REC to rise by 0.32%. According to Ansolabehere and Konisky (2016), Ballew et al. (2019), Bergquist and Warshaw (2019), Bord et al. (2000), Krosnick et al. (2000), Shwom et al. (2015), Hamilton and Keim (2009), Schuldt et al. (2011), Shao (2017), this finding is in line with American attitudes towards global warming.

Our main source for meeting the current energy demand is fossil fuels. Renewable energy might reduce the over-dependence of fossil fuels and mitigate environmental degradation. Since the recent Russia-Ukraine crisis, crude oil prices have risen, which could be a major factor in the transition from fossil fuels to renewable energy. According to my estimation, a $1 increase in the price of crude oil will increase REC by 0.011%, which is in line with the findings of Bowden and Payne (2010). Given that it will take some time to replace our excessive reliance on fossil fuels, the impact on REC is extremely minimal, which is understandable.

Greater knowledge, innovation, policy support, entrepreneurship, and skilled labor should all result from higher human capital, which should help enhance renewable energy consumption. We also discovered a beneficial effect of human capital on the REC in this study. The REC would rise by 0.0001% for every 1% increase in the proportion of college graduates or other degree holders in the labor force.

The Energy and Environmental Regulation Index can be crucial in driving renewable energy consumption by promoting favorable policies, attracting investments, facilitating policy benchmarking, raising

Table 6 Long-run ARDL Model Estimation

Variables	(1) ARDL	(2) DOLS	(3) FMOLS
Log (Awareness Level)	.3156*** (.0746)	.1985*** (.0424)	.0917*** (.0316)
Climate Extreme	-.0001 (.0020)	.0001 (.0014)	-.0001 (.0001)
Renewable Energy Investment	-.0009 (.0053)	.0036 (.0036)	.0057* (.0030)
Crude Oil Price	.0011** (.0005)	.0013** (.0004)	.0015*** (.0003)
Log (Newspaper Coverage)	-.7028*** (.1710)	-.5349*** (.1116)	-.3030*** (.0719)
Palmer Drought Severity Index	-.0051 (.0047)	-.0023 (.0037)	.0010 (.0036)
College Graduates	.0001*** (.0000)	.0001*** (.0001)	.0001*** (.001)
Energy And Environmental Regulation	.0017* (0.0010)	.0005 (.0006)	0.0001 (0.0003)
Constant		4.1646*** (0.3127)	4.5856*** (0.2374)

Note: The standard errors are in parenthesis and 10%, 5%, and 1% significant level are denoted by *, ***, *** respectively.

public awareness, and supporting technological advancements. In this study, the Energy and Environmental Regulation Index has a beneficial effect on the REC as well; a 1% increase in the index would result in a 0.0017% increase in the REC.

News coverage in newspapers can positively and negatively affect renewable energy consumption. This study finds a negative relationship between newspaper coverage of climate change and the REC in the U.S. A 1% increase in the volume of newspaper coverage about climate change would decrease renewable energy consumption by 0.70%. News coverage can raise awareness about the importance of transitioning to renewable energy sources and the urgent need to address climate change, but it can also have negative impacts in certain cases. Here are some ways in which news coverage can potentially negatively affect renewable energy consumption:

Misinformation and Skepticism: Some newspapers may publish articles or opinion pieces that spread misinformation about climate change or renewable energy technologies. This can lead to skepticism and confusion among the public, making them less likely to support or invest in renewable energy solutions.

Political Bias: News coverage can sometimes be influenced by political bias, with certain media outlets promoting anti-renewable energy narratives due to their alignment with specific political or economic interests. This can create a polarized environment in which the adoption of renewable energy becomes a divisive political issue rather than a solution to climate change.

Focus on Challenges: News coverage often emphasizes the challenges and setbacks in renewable energy adoption, such as technological limitations, cost barriers, or intermittent energy production. While it is important to acknowledge these challenges, excessive focus on them without highlighting the progress and benefits of renewable energy can deter people from supporting or investing in it.

Lack of Coverage: In some cases, newspapers may not provide sufficient coverage of renewable energy success stories, breakthroughs, or positive developments. This can create a perception that renewable energy is not making meaningful progress or that it is not a viable solution, discouraging individuals and businesses from pursuing renewable energy options.

Dependence on Fossil Fuel Advertising: Some newspapers rely on advertising revenue from fossil fuel companies, which can influence their editorial decisions and lead to biased coverage that downplays the importance of renewable energy and climate change mitigation efforts.

It's important to note that the impact of news coverage on renewable energy consumption can vary depending on the specific media outlet, the region, and the individual reader's perspective. While negative coverage can potentially hinder progress, responsible and accurate reporting can also inform and inspire individuals and communities to take action in support of renewable energy and climate change mitigation. Promoting balanced and evidence-based journalism is crucial in addressing these potential negative effects.

In the second and third columns, I present the estimations of cointegrating equations involving the utilization of the dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) methodologies, as suggested by Kao and Chiang (2001). These methodologies aim to assess or measure the enduring association between the variables. The DOLS strategy effectively addresses the issue of endogeneity and mitigates the presence of serial correlation that is inherent in the conventional ordinary least squares (OLS) method. According to Dreger and Reimers (2005), the ordinary least squares (OLS) estimation exhibits inconsistency when applied to cointegrated panel series data. The DOLS and FMOLS results in columns two and three are consistent with the ARDL estimations.

3.9 Short-run ARDL Model Estimation

With a value of -0.3655 Table 7, an ECM coefficient in the short run is statistically significant at a 1% level. This suggests that 36.55 percent of the short-run disequilibrium was corrected in the current year, indicating that the short-run distortion must be adjusted toward the long-run equilibrium path. I discover that the short-run aberrations from the long-run equilibrium are annually adjusted by 36.55%.

Most lagged forms of variables are not significant in the short run. Unexpectedly, the first lag of the REC and the first and second lag of awareness level of climate change have a detrimental impact on the current REC. The use of renewable energy in the present generally is not adversely affected by the use of renewable energy in the past. However, there are a few indirect ways in which past levels of renewable energy use could have a negative impact on the present year, such as infrastructure and grid capacity, lower returns from renewable energy investments, and less stringent environmental and energy legislation.

While climate extremes can have devastating consequences, they can also provide opportunities to advance renewable energy adoption. By leveraging these opportunities and addressing the challenges posed by climate extremes, societies can accelerate the shift towards sustainable and resilient energy systems. According to my ARDL estimation, the second and third lags of climate extremes have a positive effect on renewable energy consumption, meaning that as climate extremes increase now, we will use more renewable energy in the future.

Furthermore, this study finds that the first lag of newspaper coverage in climate change negatively affects REC. While news coverage can raise awareness about the importance of transitioning to renewable energy sources, lack of coverage, misinformation and skepticism, political bias, framing, and sensationalism might negatively impact REC.

Table 7 Short-run ARDL Model Estimation

Regressors	Coefficients	Std. Error	T-Statistics
ECM	-.3655***	.0712	-5.13
lnREC(-1)	.4722***	.0750	6.29
lnREC(-2)	.1291	.0876	1.46
lnREC(-3)	.0882	.0713	1.01
lnAL	-.00196	.0202	-0.10
lnAL(-1)	.0746***	.0218	3.41
lnAL(-2)	.0106	.0224	0.47
lnAL(-3)	.0112	.0229	0.53
lnAL(-4)	.0207	.0187	1.11
lnCE	-.0000	.0005	-0.03
CE(-1)	.0019***	.0006	-0.03
CE(-2)	-.0005	.0005	-0.94
CE(-3)	-.0001	.0006	-0.26
CE(-4)	-.0012***	.0005	-2.29
lnRI	-.0000	.0031	-0.02
RI(-1)	.0049	.0049	1.00
RI(-2)	-.0080	.0053	-1.50
RI(-3)	.0072	.0053	1.36
RI(-4)	-.0044	.0034	-1.31
CP	.0008	.0008	1.01
CP(-1)	.0000	.0013	0.06
CP(-2)	-.0004	.0008	-0.56
lnNC	-.0832*	.0437	-1.90
lnNC(-1)	-.0894*	.0486	-1.84
lnNC(-2)	-.0337	.0490	-0.69
lnNC(-3)	.0504	.0478	-1.05
PDSI	.0004	.0042	0.11
PDSI(-1)	-.0023	.0043	-0.55
CG	. .0001*	.0001	1.75
CG(-1)	-.0000	.0000	-0.56
CG(-2)	.0000	.0000	0.26
CG(-3)	-.0000	.0000	-0.33
CG(-4)	.0000	.0000	0.14
EER	-.0001	.0001	-0.12
EER(-1)	.0001	.0001	-0.17
EER(-2)	.0002	.0001	1.62
EER(-3)	0004**	.0001	2.38
Constant	1.3189***	.3615	3.65

Note: The standard errors are in parenthesis and 10%, 5%, and 1% significant level are denoted by *, ***, *** respectively.

4 Diagnostic Tests

Before starting any econometric analysis, diagnostic testing is essential to ensure that the estimated model is accurate. Additionally, to proceed with the analysis of the model's output, some diagnostic tests are conducted to judge the stability of the model, including the heteroscedasticity test, serial correlation test (Brush & Godfray LM test), normality test (Jaque-Bera test), and functional form test (Ramsey's RESET test). As displayed in the accompanying Table 8, diagnostic tests demonstrate that the long-run and short-run estimates are free of serial correlation, short-run model misspecification, non-normality of the error component, and heteroscedasticity.

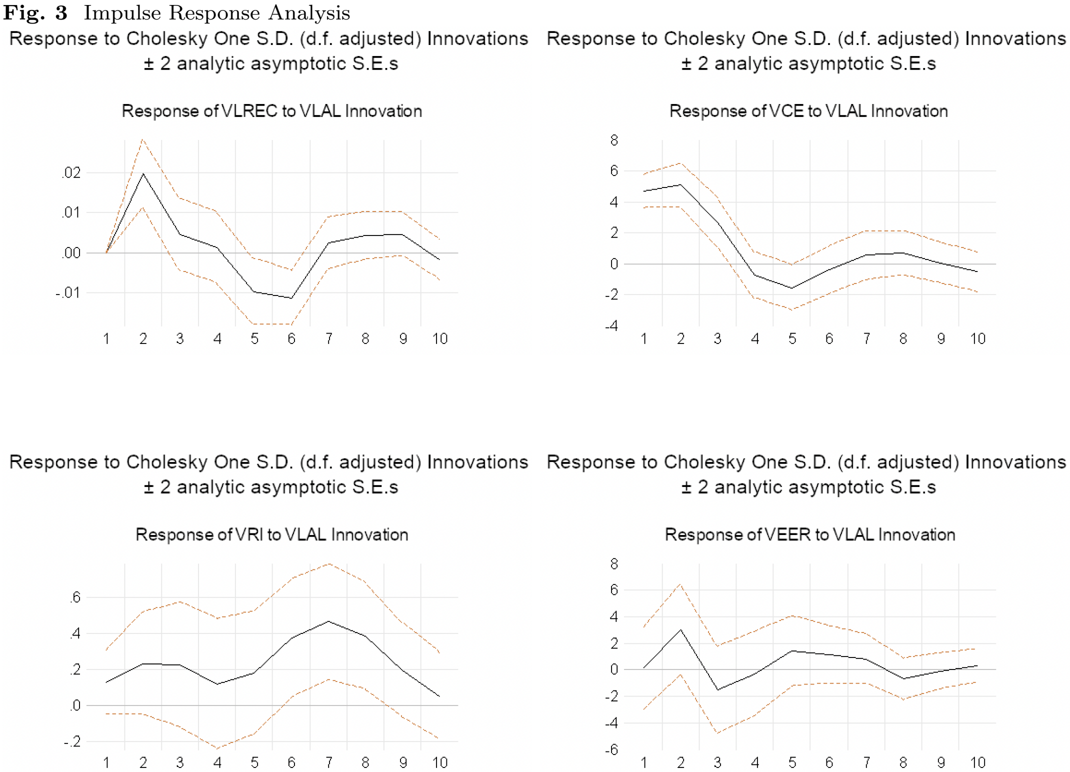
Table 8 Diagnostic Tests

Diagnostic test	p-value	Result
Breusch-Godfrey LM	0.5183	No serial correlations
White test	0.4667	No heteroskedasticity
Ramsey RESET test	0.9	Model is specified correctly
Normality test	0.1938	Estimated residual are normal

4.1 Impulse Response Analysis

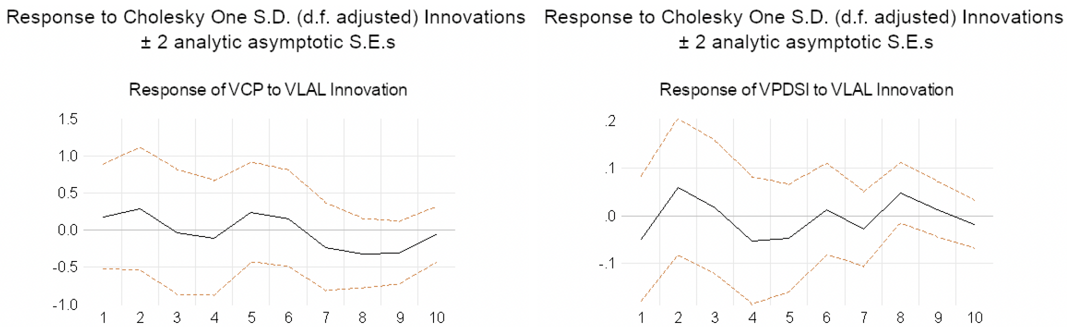
In econometric analysis, using vector autoregressive models is a crucial mechanism to analyze shocks in variables. This study uses structural vector autoregressive (SVAR) Models for the impulse response analysis. The major goal is to outline how renewable energy usage changed in response to increased public awareness of climate change. In this study, I utilize the difference and demeaning techniques to analyze responses from a shock in the awareness level.

Fig. 3 Impulse Response Analysis



From Figure 3, we can observe a relationship between renewable energy consumption and awareness level. One standard deviation increase in awareness level due to shock leads to a 0.03 standard deviation increase in the REC—however, it starts decreasing in the following period. Furthermore, after five periods, it dies out.

Furthermore, one standard deviation increase in AL causes a 5 standard deviation increase in the CE but starts declining after the first period and dies out eventually. Massive infrastructure buildings might cause an initial increase in generating renewable energy using fossil fuels. But the environment turns

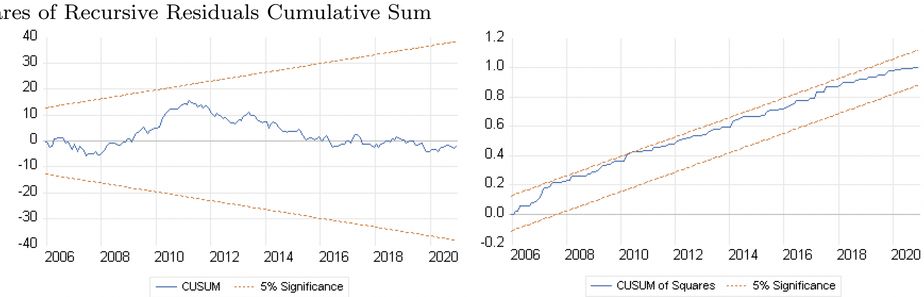


better after transitioning to renewable energy. Investment in renewable energy is affected positively and negatively within our ten periods. However, there is not much response in the rest of the variables.

4.2 Parameter Stability Test

For both long-run and short-run relationships, the stability of the model is assessed using the CUSUM and CUSUMSQ tests at 5% significance level. This test is useful for detecting sudden changes in the coefficient of regression. Therefore, if the blue line crosses the red line, a critical line, and never goes back between the two critical lines, we accept the null hypothesis of parameter instability. However, parameter stability exists in both the short- and long-term if the cumulative sum falls inside the region (which can revert back) between the two critical lines.

Fig. 4 Squares of Recursive Residuals Cumulative Sum



The figure shows that the CUSUM and CUSUMSQ test reveals that the graphs do not cross the bottom and upper critical limits. There is no structural breach, and long-term estimates are stable as a result.

4.3 Granger Causality Test

The Granger causality test using vector autoregression was employed in this study to ascertain the direction of causation between cointegrated variables to track the long-run causality among pertinent variables (Kyophilavong, Uddin, and Shahbaz (2016)). In other words, one can deduce the long-term relationship by looking at the significance of the lagged error correction terms. Therefore, for long-run causation to occur, ECT coefficients must be negative and statistically significant.

Table 9 Granger Causality Test

Null Hypothesis	chi^2	P-value
Log(Awareness Level) does not granger cause Log(REC)	33.996	0.000
Log(Renewable Energy Consumption) does not granger cause Log(AL)	8.0506	0.1115

Whether or not two variables are cointegrated determines the necessary conditions for evaluating Granger causality in the long run based on vector error correction (Tamba, Koffi, Lissouck, Ndame, and Afuoti (2014)).

As a consequence, the Granger causality test indicated from the results above demonstrates that the level of climate change consciousness is crucial for the consumption of renewable energy in the United States, which confirms the augment of awareness leads the REC hypothesis in the long run at 95% level.

5 Conclusion And Policy Implications

In this study, I investigate the impact of awareness levels about climate change on renewable energy consumption. I employ a mix of micro and macro approaches to derive causality. Firstly, I conduct a survey among Texas college students to gauge their awareness levels of climate change and willingness to pay for renewable energy. The results underscore a compelling linkage: students with heightened awareness levels of climate change are 23% more inclined to pay a premium for renewable energy. Additionally, I find that at least 80% of students are aware of environmental issues and renewable energy, 87% believe the state should educate citizens about climate change, renewable energy, and environmental protection, and around 50% of them want to pay at least $0.20 per gallon more for gasoline. Building upon these individual-level insights, I extrapolate the findings to a macroeconomic context using national-level data. Utilizing autoregressive distributed lag modeling on a time series data set from 2004 to 2020, I form a macroeconomic analysis and find the dynamics between awareness and renewable energy consumption. My analysis reveals that a 1% increase in awareness level corresponds to an increase in renewable energy consumption by 0.32% but a $1 increase in the average oil price corresponds to a mere 0.002% increase in REC adoption. The rationale underpinning this relationship lies in the premise that surging oil prices render fossil fuels more expensive, prompting some consumers and industries to explore alternatives, including renewable energy. However, this transition involves substantial upfront costs, deterring immediate adoption due to economic uncertainties stemming from elevated oil prices despite the long-term cost savings and environmental benefits associated with renewable energy.

Since there is low substitutability between oil and renewable energy sources, the climate awareness level is potentially very low. To answer a policy question on how to raise awareness among U.S. adults, I focus on the newspapers due to their formidable influence on public opinion, which possess the potential to either bolster or hinder the adoption of renewable energy sources. In this vein, this research furnishes empirical evidence that newspaper coverage of climate change can exert a detrimental influence on renewable energy consumption. Specifically, for every 1% increment in the overall volume of climate change articles in prominent newspapers, there is a corresponding 4.63% decrease in renewable energy usage.

Education can serve as a catalyst for promoting awareness and enhancing the adoption of renewable energy by providing individuals with the necessary knowledge, skills, and motivation to support and embrace sustainable practices. Additionally, it plays a role in a wider societal transition towards a more sustainable and ecologically aware future. This analysis reveals a positive correlation between a 1% rise in the number of individuals with college degrees and a 0.002% increase in the utilization of renewable energy. College graduates, as a group, typically demonstrate increased awareness and concern for the environment and, hence have the potential to play a role in the gradual shift towards more sustainable energy sources.

Given that renewable energy is a key substitute for fossil fuels, the cost of fossil fuels becomes a crucial determinant in energy-related decision-making. Theoretically, as postulated by Moriarty and Honnery (2016) and Dincer and Rosen (2004), an escalation in fossil fuel prices should constrict demand for fossil fuels and drive the adoption of renewable energy. In the purview of this study, my findings underscore a positive association between oil prices and renewable energy consumption. Specifically, a $1 increase in the average crude oil price corresponds to a mere 0.002% increase in REC adoption. The rationale underpinning this relationship lies in the premise that surging oil prices render fossil fuels more expensive, prompting some consumers and industries to explore alternatives, including renewable energy. However, this transition involves substantial upfront costs, deterring immediate adoption due to economic uncertainties stemming from elevated oil prices despite the long-term cost savings and environmental benefits associated with renewable energy.

Furthermore, I explore the pivotal role of energy and environmental regulations in shaping renewable energy consumption. These regulations, as institutional frameworks, serve as essential drivers for the development and adoption of clean energy sources. Their potency is grounded in their ability to set renewable energy targets, offer financial incentives, and impose emissions limits, thereby stimulating investments by businesses and individuals. These regulations also level the playing field, rendering clean energy more competitive with traditional fossil fuels. My findings, however, underscore that the impact of regulations can be gradual. The implementation of regulatory changes is often mired in intricate legislative processes, leading to delays. Opposition from industry stakeholders, political resistance, budget constraints, and infrastructure development further contribute to the protracted regulatory impact. Additionally, the long-term nature of renewable energy projects, characterized by substantial upfront costs and extensive infrastructure development, implies that the effects of regulations may only manifest over an extended period. While regulations are incontrovertibly pivotal in driving renewable energy adoption, their effects can be incremental, underscoring the need for sustained commitment and perseverance.

The significance of these findings extends to policymakers and scholars due to their contribution to addressing a research gap and investigating the effectiveness of aid in relation to environmental policies and energy use inside the United States. According to my analysis, Americans are becoming increasingly motivated to combat climate change and are willing to pay more for renewable energy sources. Consequently, the policy implications of this observation indicate that more stringent environmental rules and taxation measures are likely to be embraced in the endeavour to combat climate change.

References

Alvarado, R., Ponce, P., Alvarado, R., Ponce, K., Huachizaca, V., Toledo, E. (2019). Sustainable and non-sustainable energy and output in latin america: A cointegration and causality approach with panel data. *Energy Strategy Reviews*, *26*, 100369,

Ansolabehere, S., & Konisky, D.M. (2016). *Cheap and clean: how americans think about energy in the age of global warming.* Mit Press.

Apergis, N., & Payne, J.E. (2010). Renewable energy consumption and economic growth: evidence from a panel of oecd countries. *Energy policy*, *38*(1), 656–660,

Atems, B., & Hotaling, C. (2018). The effect of renewable and nonrenewable electricity generation on economic growth. *Energy Policy*, *112*, 111–118,

Ballew, M.T., Leiserowitz, A., Roser-Renouf, C., Rosenthal, S.A., Kotcher, J.E., Marlon, J.R., ... Maibach, E.W. (2019). Climate change in the american mind: Data, tools, and trends. *Environment: Science and Policy for Sustainable Development*, *61*(3), 4–18,

Bergquist, P., & Warshaw, C. (2019). Does global warming increase public concern about climate change? *The Journal of Politics*, *81*(2), 686–691,

Bord, R.J., O'connor, R.E., Fisher, A. (2000). In what sense does the public need to understand global climate change? *Public understanding of science*, *9*(3), 205,

Bowden, N., & Payne, J.E. (2010). Sectoral analysis of the causal relationship between renewable and non-renewable energy consumption and real output in the us. *Energy Sources, Part B: Economics,* *Planning, and Policy*, *5*(4), 400–408,

Brini, R., Amara, M., Jemmali, H. (2017). Renewable energy consumption, international trade, oil price and economic growth inter-linkages: The case of tunisia. *Renewable and Sustainable Energy Reviews*, *76*, 620–627,

Caretta, A.M.M.A., Arfanuzzaman, R.B.M., Morgan, S.M.R., Kumar, M., et al. (2022). Water. in: Climate change 2022: Impacts, adaptation, and vulnerability. contribution of working group ii to the sixth assessment report of the intergovernmental panel on climate change.

Carleton, T.A., & Hsiang, S.M. (2016). Social and economic impacts of climate. *Science*, *353*(6304), aad9837,

Chawla, L. (1998). Significant life experiences revisited: A review of research on sources of environmental sensitivity. *The Journal of environmental education*, *29*(3), 11–21,

Dickey, D.A., & Fuller, W.A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427–431,

Dincer, I., & Rosen, M.A. (2004). Exergy as a driver for achieving sustainability. *International journal of green energy*, *1*(1), 1–19,

Dogan, E., Altinoz, B., Madaleno, M., Taskin, D. (2020). The impact of renewable energy consumption to economic growth: a replication and extension of. *Energy Economics*, *90*, 104866,

Dreger, C., & Reimers, H.-E. (2005). Health care expenditures in oecd countries: a panel unit root and cointegration analysis. *Available at SSRN 651985*, ,

Graff Zivin, J., & Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, *51*(3), 689–730, Hamilton, L.C., & Keim, B.D. (2009). Regional variation in perceptions about climate change. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *29*(15), 2348–2352,

Hosmer, D., Lemeshow, S., Sturdivant, R. (2000). *Applied logistic regression. hoboken, nj: John whiley and sons.* Inc.

Hungerford, H.R., & Volk, T.L. (1990). Changing learner behavior through environmental education. *The journal of environmental education*, *21*(3), 8–21,

Isen, A., Rossin-Slater, M., Walker, R. (2017). Relationship between season of birth, temperature exposure, and later life wellbeing. *Proceedings of the National Academy of Sciences*, *114*(51), 13447–13452,

Jalil, A., & Ma, Y. (2008). Financial development and economic growth: Time series evidence from pakistan and china. *Journal of economic cooperation*, *29*(2), 29–68,

Jeske, W.E. (1978). *Toward an action plan: A report on the intergovernmental conference on environmental education.* Department of Health, Education, and Welfare, Office of the Assistant . . . .

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. *Oxford Bulletin of Economics and statistics*, *52*(2), 169–210,

Kao, C., & Chiang, M.-H. (2001). On the estimation and inference of a cointegrated regression in panel data. *Nonstationary panels, panel cointegration, and dynamic panels* (pp. 179–222). Emerald Group Publishing Limited.

Khan, M.I., Yasmeen, T., Shakoor, A., Khan, N.B., Muhammad, R. (2017). 2014 oil plunge: Causes and impacts on renewable energy. *Renewable and Sustainable Energy Reviews*, *68*, 609–622,

Krosnick, J.A., Holbrook, A.L., Visser, P.S. (2000). The impact of the fall 1997 debate about global warming on american public opinion. *Public Understanding of Science*, *9*(3), 239, Kyophilavong, P., Uddin, G.S., Shahbaz, M. (2016). The nexus between financial development and economic growth in lao pdr. *Global Business Review*, *17*(2), 303–317,

Lučkaničová, M., Ondrušeková, I., Rešovsky, M. (2012). Employment modelling in slovakia: Comparing logit models in 2005 and 2009. *Economic Annals*, *57*(192), 25–39,

Luqman, M., Ahmad, N., Bakhsh, K. (2019). Nuclear energy, renewable energy and economic growth in pakistan: Evidence from non-linear autoregressive distributed lag model. *Renewable energy*, *139*, 1299–1309,

Moriarty, P., & Honnery, D. (2016). Can renewable energy power the future? *Energy policy*, *93*, 3–7,

Narayan, P. (2004). *Reformulating critical values for the bounds f-statistics approach to cointegration: an application to the tourism demand model for fiji* (Vol. 2) (No. 04). Monash University Australia.

Nordhaus, W.D. (2007). A review of the stern review on the economics of climate change. *Journal of economic literature*, *45*(3), 686–702,

Omri, A., & Nguyen, D.K. (2014). On the determinants of renewable energy consumption: International evidence. *Energy*, *72*, 554–560,

Park, R.J., Behrer, A.P., Goodman, J. (2021). Learning is inhibited by heat exposure, both internationally and within the united states. *Nature human behaviour*, *5*(1), 19–27,

Pesaran, M.H., Shin, Y., Smith, R.J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289–326,

Pesaran, M.H., Shin, Y., Smith, R.P. (1999). Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American statistical Association*, *94*(446), 621–634, Pesaran, M.H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of econometrics*, *68*(1), 79–113,

Sadorsky, P. (2009). Renewable energy consumption, co2 emissions and oil prices in the g7 countries. *Energy Economics*, *31*(3), 456–462,

Said, S.E., & Dickey, D.A. (1984). Testing for unit roots in autoregressive-moving average models of unknown order. *Biometrika*, *71*(3), 599–607,

Schuldt, J.P., Konrath, S.H., Schwarz, N. (2011). "global warming" or "climate change"? whether the planet is warming depends on question wording. *Public opinion quarterly*, *75*(1), 115–124,

Shao, W. (2017). Weather, climate, politics, or god? determinants of american public opinions toward global warming. *Environmental Politics*, *26*(1), 71–96,

Shwom, R.L., McCright, A.M., Brechin, S.R., Dunlap, R.E., Marquart-Pyatt, S.T., Hamilton, L.C. (2015). Public opinion on climate change. *Climate change and society: Sociological perspectives*, *269*, 299,

Slemrod, J., Gale, W.G., Easterly, W. (1995). What do cross-country studies teach about government involvement, prosperity, and economic growth? *Brookings papers on economic activity*, *1995*(2), 373–431,

Tamba, J.G., Koffi, F.D., Lissouck, M., Ndame, M., Afuoti, N.E. (2014). A trivariate causality test: A case study in cameroon. *Applied Mathematics*, *2014*, ,

Tanner, T. (1980). Significant life experiences: A new research area in environmental education. *The Journal of Environmental Education*, *11*(4), 20–24,

Tracker, C.A. (2022). Warming projections global update november 2022.

Wang, W., Wang, S., Ma, X., Gong, J. (2011). Recent advances in catalytic hydrogenation of carbon dioxide. *Chemical Society Reviews*, *40*(7), 3703–3727,

Wooldridge, J.M. (2015). *Introductory econometrics: A modern approach.* Cengage learning.

Zafar, M.W., Shahbaz, M., Hou, F., Sinha, A. (2019). From nonrenewable to renewable energy and its impact on economic growth: the role of research & development expenditures in asia-pacific economic cooperation countries. *Journal of cleaner production*, *212*, 1166–1178,