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RESEARCH ARTICLE

Towards Carbon Neutrality: The Impact of Private AI Investment and Financial Development in the United States – An Empirical Study Using the STIRPAT Model

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Abstract
This investigation analyses the influence of private AI investment and financial development (FD) on CO2 emissions in the United States, using the STIRPAT framework to account for the functions of GDP, population, and foreign direct investment (FDI). The data's robustness was verified through the application of a variety of unit root tests, which confirmed that the variables are free of unit root issues and exhibit a varied order of integration. The ARDL bound test was used to investigate the cointegration among the variables and it found a long-run equilibrium relationship. The ARDL model results show that income, FDI, FD, and population significantly increase CO2 emissions in both the short and long term. In contrast, we found that private investment in AI led to a significant reduction in CO2 emissions over these time frames. Additional estimations were conducted using FMOLS, DOLS, and CCR methods to verify the ARDL results, all of which attested to the initial findings' robustness. In addition, the study implemented a pairwise Granger causality test to illustrate the directional relationships between the variables. There is a unidirectional causal link between GDP, private AI investment, FDI, population, and CO2 emissions, according to the findings. Most notably, we observed bidirectional causality between CO2 emissions and FD. Diagnostic tests further corroborated the validity of the study's conclusions, confirming that the model is free from specification errors, serial correlation, and heteroscedasticity.

Keywords: Private AI Investment; Financial Development; FDI; Carbon Neutrality; United States

Introduction

Researchers from all around the world have been discussing and analyzing environmental economics and global warming for a few decades (Abid et al., 2022). Growing urbanization and industrialization have brought about significant environmental changes in recent decades (Mehmood and Tariq 2020). People widely recognize CO2 emissions as the primary proxy of ecosystem damage (Voumik et al., 2024). UN research predicts that the 2015 Paris Agreement's aims for limiting global disasters may not be achieved if emissions of CO2 aren't drastically cut below 2°C and 1.5°C. Serious social and economic repercussions will follow the failure to meet the carbon mitigation target (Ridwan et al., 2024). With 6677 million metric tons of CO2, CO2 accounted for 81.3% of all GHG pollution in 2018 (EPA, 2020). Of the GHGs released in 2018, 22% came from industrial activity alone or predominantly (EIA, 2020). In 2021, the US possessed the largest economy and ranked second in terms of CO2 emissions among developed nations (British Petroleum 2022; World Bank 2022). In this sense, AI approaches can predict CO2 emissions, and contemporary technology can guarantee environmental sustainability. Moreover, Wang et al. (2019) demonstrated that there is no longer an association within CO2 pollution and economic growth, as the US GDP increased by 19% between 2007 and 2016. Given the United States' large scale and high CO2 emissions, further investigation is necessary to explore the correlation between CO2 emissions and GDP (Ulussever et al., 2023). Therefore, it is required to demonstrate the relationship across private investment in AI (PAI), financial development (FD), and CO2 emissions within the framework of the US, since this can potentially provide guidance for other countries. Therefore, we give special consideration to FD, FDI, and PAI due to their potential to increase CO2 emissions in this country. Scholars have conducted a thorough analysis of the United States' ecological state of circumstances (Acheampong, 2018). Since it draws attention to the harmful effects that our behavior has on the ecosystem, we applied it as a demand-side measure of environmental degradation. The United States has set a goal to achieve carbon neutrality, which means reaching a state where the level of GHGs generated is equivalent to the amount eliminated by the atmosphere by no later than 2050. US President Biden announced the US's return to the Paris Agreement in 2021 with the Clean Energy Revolution and Environmental Justice Plan, which seek for a green energy economy and a net zero CO2 emission by goal by 2050 (Harris, 2020). The state governments are eager to take some concrete steps against global warming to meet this objective (Dehdar et al., 2023). To achieve the SDGs, an economy must employ an effective policy to minimize CO2 emissions in addition to controlling finances (Yu et al., 2024). Although the US boasts the eighth-highest GDP per capita among 189 countries, its financial system face significant challenges due to the overuse of natural assets and CO2 emissions (Zafar et al., 2019). The expansion of GDP correlates with an upsurge in CO2 pollutions (Raihan et al., 2024b). Moreover, industrial revolution led to a substantial rise in the use of AI, and its implication on energy usage and CO2 releases could aid in the attainment of carbon neutrality. Furthermore, AI algorithms that decrease CO2 emissions contribute to the emergence of the sustainable financial system. By implementing strategies such as optimizing industrial structure, updating networks, and supporting creativity in sustainable technologies can effectively cut CO2 emissions. However, by enabling technology transfer to recipient nations, FDI promotes the formation of human resources and the spread of innovation (Shahbaz et al., 2019). Furthermore, it promotes the use of manufacturing goods that pollute the natural environment and spread industrial activity while also aiding in the GDP development of the host region (Balli et al., 2023). Furthermore, FD can encourage the purchase of expensive items like automobiles, houses, and other objects, leading to higher power use, manufacturing, and CO2 emissions (Dogan and Turkekul, 2016). Conversely, when individuals rapidly depend on fossil fuels to enhance their quality of life, the planet suffers. Consequently, countries experiencing a surge in population will exhibit higher levels of CO2 emissions (Esquivias et al., 2022). Our paper significantly contributes to the corpus of expertise currently available on ecosystem degradation in several important areas. First, it introduces a new method for analyzing short- and long-term implications on the US zone by breaking down the

STIRPAT model and combining it with the ARDL framework. We particularly scrutinize the possible determinants of CO2 emissions, namely PAI, FDI, and FD. Furthermore, by employing a relatively new dataset that encompasses a thorough investigation from 1996 to 2022 in the United States, our work contributes to the abundance of research already available on the environmental effects of PAI, FDI, and FD. Second, we use traditional unit root tests like ADF, P-P, and DF-GLS to assess the factors' stationarity. Third, we implement the ARDL bounds technique to cointegration to determine if there exists a cointegrating connection between CO2 emissions and their driving factors. We then use Granger causality tests to look at the causal connection among the selected factors. Lastly, we applied various approaches such as FMOLS, DOLS, and CCR, along with additional diagnostic instruments, to evaluate the validity of our results and address any potential issues with the dataset. This research shows that while GDP, FDI, and population all influence emission levels in the USA, FDI and PAI enhance environmental level by cutting CO2 emissions. This document arranges the remaining sections in the following order: Part 2 briefly represents the prior literature, while the next subsection illustrates the empirical model and information. The 4th portion provides the methodology. The 5th part displays the findings and critiques, the 6th chapter provides the conclusion, and Section 7 finally discusses the policy implications.

Literature Review

Several current studies focus on the complex links between CO2 emissions, GDP progress, FDI, AI investment, FDI, and population expansion in different locations globally. We review the current state of academic research in that area to identify any gaps in the existing body of knowledge. Moreover, we are trying to ascertain the novel and significant sides of our research that add to this continuously expanding field of study. Given the magnitude of global warming, it is essential to evaluate CO2 emissions by employing a diverse array of mathematical models and theories (Ridwan et al., 2023). The consumption of non-renewable energy and the loss of forests are rising, which leads to climate change, there has been an enormous rise in the number of studies focusing on CO2 emissions in recent years (Jaafar et al., 2020). Raihan et al. (2024c) conducted an experiment in Vietnam to look at the correlation between economic development and CO2 release. They concluded that there is a direct connection between GDP growth and CO2 emissions, using the DOLS technique. Raihan et al. (2022b) have established a clear correlation, indicating that in the United States, a 1% expansion in GDP causes a corresponding surge of 0.59% in CO2 pollutions in the short term and 0.29% in the long run. Ahmad et al. (2024) utilized the ARDL bound test for cointegration to explore the impact of GDP on China's ecological degradation. They demonstrated that a 1% boost in GDP corresponds to a 0.51% increase in CO2 emissions. In addition, Pattak et al. (2023) provide evidence that corroborates the findings of previous studies. They observe that a 1% expansion in Italian GDP over an extended time can leads to an 8.08% spike in CO2 emissions. Raihan et al. (2023a) investigate the ecological impacts of China's nuclear energy usage from 1993 and 2022, focusing on the EKC and PHH. They demonstrated that the expectation is that reducing CO2 emissions will improve environmental quality and accelerate GDP growth. Similarly, Mehmood et al. (2021) determined that the autonomous influence of GDP significantly reduces the CO2 emissions of Bangladesh and Pakistan. Contrarily, Acheampong et al. (2022) employed the NARDL approach and found that there is a minimal distinction between the increase and decrease in GDP in relation with CO2 pollutions. Numerous papers discussed the deployment of AI and ML to lessen CO2 emissions in construction sectors (Peng, 2019). A sizable number of studies have employed patent filings as a stand-in for invention (Balsalobre-Lorente et al., 2018; Herrerias et al., 2016). AI models, such as ML models, use data to create strategies for reducing pollution of CO2 from human activities (Delanoe et al., 2023). Similarly, Dong et al. (2023) adopted the dynamic panel data from China to create econometric models in order to look at the consequence of AI on CO2 production. Their outcome demonstrates that AI greatly lowers CO2 emissions. Conversely, empirical studies have demonstrated that robotic shocks significantly reduce CO2 emissions in

China's manufacturing industry (Chen et al., 2022; Jiang et al., 2022). From 2005 to 2016, Liu et al. (2022) looked into how artificial intelligence affected China's carbon intensity. They illustrated that AI significantly lowers carbon intensity by applying the STIRPAT framework. Zhao et al. (2023) used a fixed effects model to investigate the mechanisms and consequences of AI on China's CO2 pollutions between 2006 and 2019. The results indicate that there is a substantial drop of 6.63% in emissions for every 10% rise in the use of AI, suggesting that AI has the potential to considerably lower the intensity of pollutant emissions.

The hyperlink between FD and the quality of ecosystems has drawn the focus of a greater variety of scholars in recent years (Acheampong, 2019). The theory of FD emphasizes the impact of the monetary system on GDP growth and the potential of financial assets to contribute to sustainable development (Aghion et al., 2005). Mehmood (2024) uses the CS-ARDL methodology to evaluate the consequences of FD on CO2 emissions in Pakistan, India, Bangladesh, and Sri Lanka over the period 1984–2017. They assert that FD is essential for South Asian countries' development in order to achieve carbon neutrality. Tamazian and Rao (2010) found that FD has a major role in determining environmental performance, based on their analysis of 24 transition economies. Zafar et al. (2019) conducted a study where they examined the factors affecting the state of the earth in OECD zones. They identified a negative association between FD (which stands for a specific variable) and CO2 emissions. This means that as FD increases, the ecological health of the environment would deteriorate due to increased pollution. Nevertheless, Rjoub et al. (2021) noted that FD made more environmental pollution of Turkey. Suhrab et al. (2023) analyze the impact of FD on CO2 emissions in Pakistan using annual time series data from 1985 to 2018. The conclusion demonstrated a positive correlation between heightened FD and elevated levels of CO2 pollutions. At the same way, Shahbaz et al. (2023) examine the effects of FD and GDP growth on ecological health in 10 economies with the greatest natural impacts. The findings suggest that FD has a harmful effect on an ecosystem. Several studies, such as Shoaib et al. (2020) in D8 and G8 and Kihombo et al. (2021) in West Asia and the Middle East, have identified a direct correlation between financial progress and environmental harm. FDI is acknowledged as an essential environmental variable that boosts efficiency and GDP by progressing innovation and capital creation (Alvarado et al. 2017).The influence of FDI on ecological health varies across countries and regions, leading to conflicting findings from different research. FDI inflow, in particular, has been associated with increased ecological sustainability, primarily through technological knowledge and spillover channels (Duan and Jiang, 2021). It reduces ecosystem damage by supporting creative uses of green technologies, according to data from numerous studies (Zhu et al., 2018; Udema et al., 2020; Lahiani, 2020). Using the ARDL method, Saadaoui et al. (2024) evaluate how FDI affected Turkey's CO2 emissions from 1985 to 2021. In the nong run, the conclusions indicate that FDI mitigates emission level of CO2. Comparably, Zhang and Zhou (2016) demonstrated that FDI helps China reduce its CO2 pollutions. Wei et al. (2019) assert that FDI has the potential to enhance the natural environment by reducing pollution, but the use of green total productivity factors cannot achieve this boost. Nonetheless, increases in financial investment might encourage industrialization, which could worsen the environment and increase pollution (Baloch et al. 2019). Salahuddin et al. (2018), on the other hand, studied the empirical effects of FDI on CO2 emissions in Kuwait covering 1980 and 2013. Using the ARDL bounds testing methodology, they discovered that FDI increases CO2 emissions in both short and long terms. In a similar vein, Sapkota and Bastola (2017) discovered proof of FDI's detrimental effects on the ecosystem and indicated that a 1% spike in FDI is responsible for a 0.04% increase in ecosystem damage in Latin America. Population expansion (POP) has become a serious issue for environmental pollution, and several academicians are focusing on the nexus between boost in population and the release of CO2. It is one of the key elements causing pollution (Grigg, 1991). By deploying the sophisticated ARDL and the STIRPAT model, Voumik et al. (2023a) calculated the effects of rise in POP on CO2 pollution. The empirical data show that growing populations can raise the nation's emissions of CO2 in Kenya. According to Pachiyappan et al. (2021), there will be a 1.4%

rise in CO2 emissions in India. Furthermore, Voumik and Ridwan (2023) conducted an investigation in Argentina from 1972 to 2021 using the ARDL methodology, and the empirical conclusions revealed that population development degrades ecosystem level in the long run. In a similar way, several studies, such as Ali et al. (2020) in Malaysia and Zhang et al. (2023) in the top 10 nuclear-generating economies, found the same outcomes. But Alam et al. (2016) investigated how growth in populations in China, Brazil, India, Indonesia, and China affected CO2 emissions between 1970 and 2012. They demonstrated a statistically significant correlation between CO2 emissions and POP increase for Brazil and India, but a statistically insignificant one for China and Indonesia. Conversely, Begum et al. (2015) surprisingly showed that the pace of population growth in Malaysia had no apparent consequences on the country's per capita emissions of CO2. In contrast, Sulaiman et al. (2018) employed the ARDL model and found that population growth could only have an immediate implication on CO2 emissions in Nigeria. With its focus on the U.S. setting and its distinct socioeconomic and ecological features, this study seeks to close a large knowledge gap. Despite growing global attention to equitable development, few thorough studies in USA to look at the combined influences of population rise, FD, FDI, PAI, and GDP development on CO2 emissions. In-depth assessments of the intricate interactions between these factors tend to be absent in the literature that is currently available, especially when it comes to the STIRPAT model. The outcomes of the connection among FD, PAI, and CO2 emissions are still contradictory, even though earlier research acknowledged the necessity for more thorough investigations on these associations. But it's crucial to consider that financial innovation and private investment in AI can encourage the uptake of cutting-edge, environmentally friendly technologies, which could assist in a decline in CO2 pollutions. Therefore, the objective of this study is to fill these gaps and provide policymakers with useful information so they can establish long-term plans to cut emissions.

Methodology

Data and Variables

Table 1 displays a full description of the data sources and relevant information. This research uses a balanced time series dataset for the United States, spanning the years 1996–2021. The Global Footprint Network (GFN) provides statistics for assessing ecological viability through CO2 emissions, which act as the dependent variable. Our World in Data provides one important parameter in this analysis: private investment in AI. The IMF provides statistics for the FD which is another important factor. The World Development Indicators (WDI) also provides population, GDP, and foreign direct investment data. We select the information sources based on their accessibility.

Theoretical Framework

The research utilizes modified IPAT and STIRPAT models for analyzing data.Ehrlich and Holdren (1971) first suggested the IPAT model as a framework for examining how growing population harms the environment. They adopted the following set of model instances:

$$I \equiv P.A.T \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

Here, "P" stands for population size, "A" for affluence, "T" for technological level, and "I" for the impact on the environment. There are several issues with the original IPAT identification. Dietz and Rosa (1994, 1997) suggested a modified format regarded as STIRPAT to address these issues. It includes a stochastic equation to account for unintentional errors in parameter estimations. The model not only incorporates factors beyond the original IPAT framework, but also enables the estimation of these factors' elasticities (Shu et al., 2024). These researchers examine the following formulation:

$$I_{it} = CP_{it}^{\gamma_1} A_{it}^{\gamma_2} T_{it}^{\gamma_3} \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

At time t, P represents the country's population, A represents its wealth, and T represents its technology. The constant term in the STIRPAT model is C, while the random error component is represented by ε. Conversely, the symbols γ_1,γ_2, and γ_3 denote the coefficients of P, A, and T, respectively.We can express the logarithmic transformation of the model as follows:

$$LnI_{it} = C + \gamma_1 LnP_{it} + \gamma_2 LnA_{it} + \gamma_3 LnT_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

The variables used in our research were waste recycling as an expression of impact (I), population growth as an indicator of population (P), affluence (estimated by GDP, FD, and FDI), and technological level (as private investment in AI). The equation can be written as:

$$CO_2 = f(GDP_{it}, PAI_{it}, FD_{it}, FDI_{it}, POP_{it}) \ldots\ldots\ldots\ldots\ldots\ldots.... (4)$$

Table 1. Source and Description of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
CO_2	CO_2 Emission	LCO_2	CO_2 Emission (kt)	GFN
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI
PAI	Private Investment in Artificial Intelligence	LPAI	Estimated Investment in AI (US$)	Our World in Data
FD	Financial Development	LFD	Financial Development Index	IMF
FDI	Foreign Direct Investment	LFDI	Net Inflows (Current US$)	WDI
POP	Population	LPOP	Population, total	WDI

The explanatory variables in this instance are GDP, PAI, FD, FDI, and POP, whereas the dependent variable is CO_2. An alternate way to describe the empirical model in logarithmic form is as follows:

$$LnCO_{2it} = \beta_0 + \beta_1 LnGDP_{it} + \beta_1 LnPAI_{it} + \beta_2 LnFD_{it} + \beta_3 LnFDI_{it} + \beta_4 LnPOP_{it} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where, $\beta_0$is the intercept term and $\beta_1, \beta_2, \beta_3, and\ \beta_4$are the coefficients of selected independent variables accordingly. The letter ε and L, stand for the natural log and the model's error term.

Empirical Methods

In this research, the DF-GLS, PP, and ADF assessments are among the most frequently used tests for unit root. Secondly, the statistical technique will employ robustness evaluations (FMOLS, DOLS, and CCR) to ensure the accuracy of the results, as well as the ARDL method to analyze cointegration across short and long periods. We then implemented the Granger causality test to explore the connection among the components, followed by a multitude of diagnostic tests.

Unit Root Test

Panel unit root testing is one approach to determining the integrational pattern for each variable, as the order incorporates all factors (Ozturk and Al-Mulali, 2015). It guarantees that the series is stationary and delivers an approximation of the regression equation employing stationary approaches (Raihan et al., 2023b). The standard unit root assessments that determine the sequence of variable integration include the P-P (Phillips and Perron 1988), the ADF (Dicky and Fuller 1979), and the DF-GLS test developed by Dickey-Fuller (Elliott et al., 1992). In comparison to the Dickey-Fuller (DF), the ADF technique is more robust and suited to more complicated procedures (Fuller, 2009).

ARDL Methodology

We use the cointegration and bounds testing approaches to determine whether there is a long-term link among CO2 emissions and their determinants, following the findings of the unit root analyses. Pesaran et al. (2001) recommended that the ARDL bounds test be deployed in this investigation to document the sequence's cointegration. Its main advantage is the ability to evaluate both short and long-term factors simultaneously. This allows it to analyze a wide range of time series data without requiring extensive previous testing (Raihan et al., 2022a). Furthermore, this framework (Raihan et al., 2024a) allows for the application of I (0) or I (1), or any frictionally integrated time series variable these variables typically represent. We represent the ARDL bound test in Eq. (6) as follows:

$$\begin{aligned}\Delta LCO_{2t} = {} & \alpha_0 + \beta_1 LCO_{2t-1} + \beta_2 LGDP_{t-1} + \beta_3 LPAI_{t-1} + \beta_4 LFD_{t-1} + \beta_5 LFDI_{t-1} + \beta_6 LPOP_{t-1} \\ & + \sum_{i=1}^{q} \delta_1\, \Delta LCO_{2t-i} + \sum_{i=1}^{q} \delta_2\, \Delta LGDP_{t-i} + \sum_{i=1}^{q} \delta_3\, \Delta LPAI_{t-i} + \sum_{i=1}^{q} \delta_4\, \Delta LFD_{t-i} + \sum_{i=1}^{q} \delta_5\, \Delta LFDI_{t-i} \\ & + \sum_{i=1}^{q} \delta_6\, \Delta LPOP_{t-i} + \varepsilon_t \end{aligned} \tag{6}$$

In the ARDL limit analysis, the F-distribution and critical values proposed by Pesaran and Timmermann (2005) are used within the framework of the equation denoted by (6), where q represents the optimal lag length and Δ denotes the first difference operator. Equation (6) serves as the first step in the estimating process. Pesaran et al. (2001) suggest that long-term correlations with F-statistics that fall between the threshold values are inconclusive, but those that fall below the threshold should receive acceptance.

Robustness Check

Phillips and Hansen (1990) recommended the FMOLS examination, Park (1992) reported the CCR test, and Stock and Watson (1993) calculated the DOLS test to assess the robustness of the ARDL outcomes. Before implementing FMOLS and DOLS, the CCR (Canonical Cointegrating Regression) method serves as an excellent tool for verifying their accuracy (Sultana et al., 2023). The development of these methodologies addressed two primary concerns. Before implementing FMOLS, DOLS, or CCR, it is necessary to meet the cointegration criteria among the I(1) parameters (Raihan et al., 2023b). A second benefit of these methods is that they address issues such as serial correlation, bias from absent variables, heterogeneity, and measurement errors (Raihan and Tuspekova 2023).

Granger Causality Test

The Granger causality test is paired and evaluates the sum of the past and current values of the independent variable (X) and dependent variable (Y) (Voumik et al., 2023b). The same is true for Y and X's causal link; if the outcomes deviate from zero, then both parties are causally involved (Rahman and Majumder, 2022). The analysis used the paired Granger causality test introduced by Granger (1969), and the causal connection between Xt and Yt is depicted in the following equation.

$$E\left(Y_{t+h} \middle| J_{t,} X_t\right) = E(Y_{t+h}|J_t) \tag{9}$$

Here, Jt notation is used for the sets of information gathered from all of the outcomes up to a certain point of time (t).

Diagnostic Test

The Lagrange Multiplier (LM), Jarque-Bera (Jarque and Bera, 1987), and BPG (Breusch and Pagan, 1979) tests are important in time series analysis for making sure that model assumptions are correct and that results are stable. Since many statistical models require normally distributed errors for proper inference so the Jarque-Bera investigation can be performed. By looking for serial correlation in residuals, the LM examination ensures that errors do not converge over time and produce skewed and misleading estimations. Finally, we utilized the BPG test to confirm the heteroscedasticity, or nonconstant variance, of the residuals.

Results and Discussion

Table 2 summarizes information on a variety of factors. The average LCO2 is 15.46, with a range from 15.27 to 15.56. The mean LGDP is 10.64, with a minimum of 10.08 and a maximum of 11.15. Notably, LFDI has the highest mean (25.89), while LFD has the lowest. The standard deviations of LCO2 (0.08), LGDP (0.31), LPAI (1.66), LFD (0.13), LFDI (0.76), and POP (0.08) demonstrate the variability around the mean. LPAI is positively skewed, while LCO2, LGDP, LFD, LFDI, and POP are inversely skewed. All variables have a normal distribution with low Jarque-Bera probability values. The dataset includes 32 observations for each variable from 1990 to 2022 in the United States.

Table 2. Descriptive statistics of Variables

Variable	LCO2	LGDP	LPAI	LFD	LFDI	LPOP
Mean	15.46444	10.64393	22.0143	-0.167379	25.89841	19.4995
Median	15.45192	10.71885	21.2377	-0.096679	26.09007	19.50906
Maximum	15.56919	11.15938	25.66873	-0.081949	26.96048	19.62079
Minimum	15.27889	10.08116	20.55212	-0.520773	24.13474	19.33546
Std. Dev.	0.080244	0.318778	1.665446	0.137067	0.768762	0.086797
Skewness	-0.466593	-0.255693	0.989543	-1.662635	-0.716141	-0.311024
Kurtosis	2.635357	1.888894	2.466317	4.273768	2.616801	1.894884
Jarque-Bera	1.338404	1.994763	5.602132	16.90654	2.931032	2.144299
Probability	0.512117	0.368844	0.060745	0.000213	0.230959	0.342272
Sum	494.8622	340.6058	704.4575	-5.356143	828.749	623.9841
Sum Sq. Dev.	0.199614	3.150205	85.98507	0.582405	18.32085	0.233545
Observations	32	32	32	32	32	32

Three stationarity tests for log-transformed variables at the level and first difference form are shown in Table 3. It seems that only the population factor is stationary at level I(0) at the 1% significance thresholds in each of the three unit root evaluations. Before we took into account their initial differences, the CO2, GDP, foreign direct investment, private investment in AI, and FD were non-stationary and significant at 1% significance thresholds. Thus, the ARDL methodology should be used to conduct the evaluation today because of the heterogeneous sequence of integration.

Table 3. Results of Unit root test

Variables	ADF		P-P		DF-GLS		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LCO_2	-0.155	-4.954***	-0.371	-4.959***	-0.521	-3.980***	I(1)
LGDP	-0.878	-4.841***	-0.953	-4.829***	-0.881	-4.085***	I(1)
LPAI	-0.806	-7.505***	-1.897	-7.403***	-0.673	-6.194***	I(1)
LFD	-2.731	-4.381***	-2.087	-4.551***	-1.889	-4.650***	I(1)
LFDI	-1.793	-6.508***	-1.565	-6.615***	-0.715	-4.882***	I(1)
LPOP	-4.896***	-7.881***	-6.881***	-8.605***	-3.831***	-5.750***	I(0)

Table 4 presents the bound analysis outcomes and reports the F-statistic as 4.2150, serving as a test statistic. We categorize the critical values using the integration order of the variables (I (0) and I (1)). The critical values for I (0) and I (1) are 2.08 and 3, accordingly, at the 10% significance level. Similarly, we provide critical values for both integration orders at the 5%, 2.5%, and 1% significance levels. These demonstrate the existence of a long-term correlation across the selected indicators.

Table 4. Results of ARDL bound test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	4.2150	10%	2.08	3
k	5	5%	2.39	3.38
		2.50%	2.7	3.73
		1%	3.06	4.15

We can evaluate their long-term relationship once the bound testing procedure reveals their cointegration. Table 5 adopts the novel ARDL method to outline the effects of different variables on LCO2 in the US, both in the short and long run. We can see from the given information that, a 1% spike in economic growth, the ecological condition drops by 0.057% over the long and by 0.044% over the short term. Beside the LGDP coefficient is both positive and statistically significant, we can infer that environmental pressure rises as US economic expansion accelerates. Azam et al. (2022), Cheng et al. (2021), Zafar et al. (2022), and Chien et al. (2023) have corroborated the findings and validated the beneficial association between GDP growth and carbon pollution. Furthermore, Pradhan et al. (2024) noted that as the economy expands, so does the consumption for goods and services, which raises output and, consequently increases emissions. According to the estimated coefficient for LPAI, there is an upward trend between LCO2 and private investment in AI, which promotes ecological condition in the US. In particular, an increase of 1% in LPAI delivers a long-lasting cut in CO2 emissions of 0.056% and an immediate decrease of 0.027%. This is because inventions are critical for improving energy efficiency and lowering CO2 emissions. Khalid et al. (2023) and Shahbaz et al. (2020) supported our conclusions. Additionally, higher amounts spent on eco-friendly procedures and greener technologies lessen their destructive implications on ecosystem and improve the health of our planet (Yao et al., 2021).

Table 5. ARDL short-run and Long-run Estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Long-run Estimation				
LGDP	0.057	0.6525	0.0882	0.012
LPAI	-0.056	0.0220	-2.5419	0.023
LFD	-0.357	0.2288	-1.5627	0.003
LFDI	0.027	0.0364	2.7630	0.025
LPOP	0.310	0.6517	2.1170	0.031
C	10.477	5.1367	3.2321	0.000
Short-run Estimation				
D(LCO2(-1))	0.127	0.1120	1.1368	0.071
D(LGDP)	0.044	0.2061	5.0596	0.001
D(LPAI)	-0.027	0.0086	-3.1973	0.015
D(LFD)	0.214	0.1352	2.5888	0.034
D(LFDI)	0.007	0.0106	-4.6978	0.000
D(LPOP)	0.2983	1.4912	2.5412	0.012
CointEq(-1)*	-0.475	0.1038	-4.5801	0.003

The calculated coefficients for LFD show an obvious inverse correlation with LCO2. This demonstrates that a 1% rise in FD generated a 0.214% short-term spike and a 0.357% long-term reduction. For this, the financial success plays a significant role in maintaining environmental sustainability in US. Numerous studies have revealed that the growth of the financial industry enhances the natural health (Saud et al., 2018; Latif and Faridi, 2023; Kartal et al., 2023). However, Pata et al. (2023) found the opposite result, holding that FD in the US had no bearing on the quality of the ecosystem. In addition, the destructive and statistically significant indications of the FDI coefficients suggest that an expansion in LFDI in both the long and short-run has a detrimental effect on environmental quality. Specifically, a 1% expansion in LFDI will result in a 0.027% and 0.007% increase in LCO2. It concludes that the present foreign direct investment of the United States is not conducive to reducing pollution; moreover, FDI can uplift the pollution level through energy consumption (Yang et al. 2020). Our findings align with Boubacar et al. (2024) in Africa, Zhang et al. (2023) in China, and Kouassi et al. (2024) across 43 African nations; they also concluded that greater FDI causes more release of CO2. Similarly, the results presented in Table 5 reveal that increased population degrades environmental quality in the US. An additional 1% expansion of LPOP will cause a 0.310% long and 0.298% short-run rise in CO2 pollutions. Our result aligns with Rehman et al. (2022) in Pakistan, Anser et al. (2020) in SAARC countries, and, Rehman et al. (2023) from a global perspective.

The inferences from the ARDL investigation are backed by the robustness findings shown in Table 6. At 1% significance threshold, the LGDP coefficients in the FMOLS, DOLS, and CCR models are statistically significant. According to FMOLS and CCR estimations, a 1% development in GDP results in a 0.196% and 0.117% boost in carbon pollutions, respectively, while DOLS reports a 0.016% cut in carbon emissions. A 1% rise in LPAI generates a corresponding drop in LCO2 of 0.045%, 0.030%, and 0.047% in FMOLS, DOLS, and CCR. In contrast, this result is significant in DOLS at the 10% level, as well as in FMOLS and CCR at the 1% level. Furthermore, in the FMOLS model, a 1% increase in LFD resulted in a 0.490% drop in LCO2. Conversely, there prevails a positive correlation, with a rise in CCR of 0.484% and a spike in DOLS of 0.352%. Furthermore, using the three estimation approaches, a 1% increase in LFDI yields an upsurge in LCO2 of 0.012%, 0.013%, and 0.010%. On the other hand, in FMOLS, a 1% rise in LPOP implies a 0.976% plunge in LCO2, which is notable at the 5% level. By comparison, DOLS and CCR predict a noteworthy 10% level of growth in emissions of 0.023% and 0.644%, respectively. The ARDL findings are in line with these contradictory responses.

Table 6. Robustness Check

Variables	FMOLS	DOLS	CCR
LGDP	0.196***	-0.016***	0.117***
LPAI	-0.045***	-0.030*	-0.047***
LFD	-0.490***	0.353**	0.484***
LFDI	0.012***	0.013**	0.010***
LPOP	-0.976**	0.023**	0.644*
C	10.678***	8.679***	10.561***

Table 7 outlines the causal relationships between various variables. This analysis reveals that LGDP does not cause LCO2, as observed by an F-statistic of 4.9537 and a p-value of 0.0154. This result suggests that, at the 5% significance level, we can reject the null hypothesis of no causal link between LGDP and LCO2. Additionally, there is evidence of one-way causation from LPAI, LFD, and LPOP to LCO2, supported by p-values below the conventional significance level. Similarly, there is a one-way causality between LCO2 and LFD, indicating that changes in LCO2 can influence LFD. Consequently, we can reject the null hypothesis of no causal relationship in these cases. On the other hand, p-values higher than the conventional limit of significance suggest that neither LLCO2 nor LGDP significantly contribute to LPAI, LFD, or LPOP, nor does LFDI contribute to LCO2. This implies that changes in LCO2 have no impact on LFD, population expansion, AI investment by the private sector, or economic growth. Furthermore, since LFFDI has no effect on LCO2, we cannot rule out the null hypothesis that these interactions lack a causal relationship.

Table 7. Granger Causality Test

Null Hypothesis	Obs	F-Statistic	Prob.
LGDP $\neq$ LCO2	30	4.9537	0.0154
LCO2 $\neq$ LGDP		0.8454	0.4413
LPAI $\neq$ LCO2	30	4.7929	0.0173
LCO2 $\neq$ LPAI		0.0127	0.9873
LFD $\neq$ LCO2	30	5.5694	0.0123
LCO2 $\neq$ LFD		0.2487	0.7817
LFDI $\neq$ LCO2	30	2.9103	0.0731
LCO2 $\neq$ LFDI		0.2741	0.0125
LPOP $\neq$ LCO2	30	4.6044	0.0198
LCO2 $\neq$ LPOP		0.6101	0.5512

Table 8 displays the results of three different diagnostic evaluations. Because the data are all conflicting, it is evident that no diagnostic method can completely rule out the null hypothesis. According to the Jarque-Bera test, the residuals exhibit a normal distribution with a p-value of 0.1074. Then, the Lagrange multiplier assessment shows that there is no serial correlation in the residuals, with a p-value of 0.4031 being higher than the usual level of significance. In the end, the BPG test confirms that there is no heteroscedasticity issue with the residuals, producing a p-value of 0.7459.

Table 8. The results of diagnostic tests

Diagnostic tests	Coefficient	p-value	Decision
Jarque-Bera test	2.3015	0.1074	Residuals are normally distributed
Lagrange Multiplier test	1.0361	0.4031	No serial correlation exits
Breusch-Pagan-Godfrey test	0.7459	0.3214	No heteroscedasticity exists

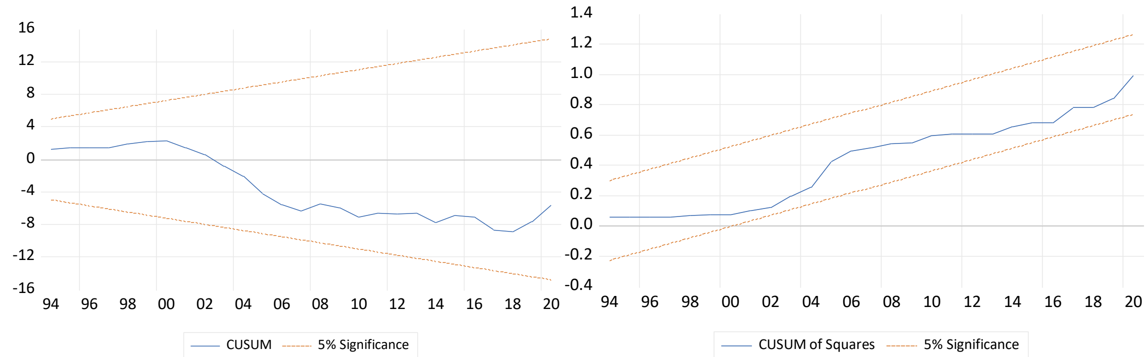

Figure 1. CUSUM and CUSUMSQ test

We performed the CUSUM and CUSUM-SQ tests to identify residuals of functions that reflect structural stability in both the short and long run. The statistical result in this case stays between the upper and lower bounds. The parameters are stable and well-defined at the 5% significant level, as evidenced by the CUSUMsq test plot's presence within the critical line (Figure 1).

Conclusion and Policy Recommendation

In the context of reaching carbon neutrality in the US, this study examines the connection among GDP growth, financial development, foreign direct investment, population growth, and private investment in AI. The analysis employs the ARDL bounds testing methodology within the STIRPAT framework using time series data spanning from 1996 to 2022. The unit root examinations confirm the stationarity of the variables and their lack of unit roots. Additionally, ARDL-bound experiments show that the factors do not cointegrate, confirming the lack of long-term equilibrium linkages. Nonetheless, the conclusions of the ARDL estimation indicate a strong and positive long-term correlation between GDP, FDI, POP, and CO2 emissions. The association between PAI and FD, on the other hand, is favorable and significant, suggesting a move toward more environmentally friendly financial practices and cutting-edge clean technology that lowers carbon emissions. According to the investigation, rising CO2 emissions in the United States are linked to economic development. However, technological and FD may be able to reduce these emissions, promoting healthy ecosystem. Robustness checks using FMOLS, DOLS, and CCR estimators validate the results, highlighting the complex relationships between these variables. Diagnostic tests confirm the regression model's reliability, and the residuals show no signs of serial correlation, heteroskedasticity, or deviations from normalcy. We also performed a Pairwise Granger causality test to investigate causal links between the variables. All things considered, this extensive investigation offers relevant details about the dynamics of development in finances, FDI, GDP expansion, AI investment, and CO2 emissions in the USA, providing a strong basis for responsible policy choices and environmental preservation plans. The findings have important policy ramifications for the United States as it strives to reconcile economic expansion with environmental sustainability. The relationship among wealth, FDI, FD, population, and CO2 emissions highlights the necessity for policies to tackle the environmental consequences of these economic activities. Law makers have to contemplate enforcing more stringent environmental restrictions on sectors that significantly contribute to CO2 emissions, particularly those that derive advantages from FDI and financial development. Moreover, the favorable influence of private investment in AI on decreasing CO2 emissions implies that advocating for AI-driven innovation might serve as a strategic means to alleviate environmental deterioration. One such approach is to provide incentives, such as tax exemptions, grants, or subsidies, to firms that invest in

AI technology with the goal of improving energy efficiency and decreasing carbon emissions. As a result, incorporating environmental risk assessments into financial decision-making processes and promoting green finance projects are critical measures to ensure that financial development is in line with sustainable environmental outcomes. Furthermore, given the one-way relationship in which GDP, FDI, and population influence CO2 emissions, it is critical to develop economic strategies that separate economic expansion from environmental damage. This may entail advocating for the adoption of the circular economy, allocating resources towards renewable energy, and raising public consciousness regarding sustainable purchasing habits. Furthermore, it is critical to ensure that urban planning and population control strategies are in line with environmental sustainability objectives, especially in densely populated regions where the population increase is more likely to worsen CO2.

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References

Abid, A., Mehmood, U., Tariq, S. et al. The effect of technological innovation, FDI, and financial development on CO2 emission: evidence from the G8 countries. Environ Sci Pollut Res 29, 11654–11662 (2022). https://doi.org/10.1007/s11356-021-15993-x

Acheampong AO, Dzator J, Amponsah M (2022) Analyzing the role of economic globalization in achieving carbon neutrality in Australia. Int J Sustain Dev World Ecol 0(0):1–20. https://doi.org/10.1080/13504509.2022.2056771

Acheampong, A. O. (2018). Economic growth, CO2 emissions and energy consumption: what causes what and where?. Energy Economics, 74, 677-692. https://doi.org/10.1016/j.eneco.2018.07.022

Acheampong, A. O. (2019). Modelling for insight: Does financial development improve environmental quality? Energy Economics, 83, 156–179.

Aghion, P., Howitt, P., & Mayer-Foulkes, D. (2005). The effect of financial development on convergence: Theory and evidence. The Quarterly Journal of Economics, 120(1), 173–222.

Ahmad, S., Raihan, A., & Ridwan, M. (2024). Role of economy, technology, and renewable energy toward carbon neutrality in China. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.04.008

Alam, M. M., Murad, M. W., Noman, A. H. M., & Ozturk, I. (2016). Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia. Ecological Indicators, 70, 466-479. https://doi.org/10.1016/j.ecolind.2016.06.043

Ali, S. S. S., Razman, M. R., & Awang, A. (2020). The nexus of population, GDP growth, electricity generation, electricity consumption and carbon emissions output in Malaysia. International Journal of Energy Economics and Policy, 10(3), 84-89.

Alvarado R, Iniguez M, Ponce P (2017) Foreign direct investment and economic growth in Latin America. Econ Anal Policy 56:176–187. https://www.sciencedirect.com/science/article/abs/pii/S1470160X14003951. Accessed 30 June 2023

Anser, M.K., Alharthi, M., Aziz, B. et al. Impact of urbanization, economic growth, and population size on residential carbon emissions in the SAARC countries. Clean Techn Environ Policy 22, 923–936 (2020). https://doi.org/10.1007/s10098-020-01833-y

Azam, A., Rafiq, M., Shafique, M., & Yuan, J. (2022). Towards Achieving Environmental Sustainability: The Role of Nuclear Energy, Renewable Energy, and ICT in the Top-Five Carbon Emitting Countries. Frontiers in Energy Research, 9, 804706.

Balli, E., Sigeze, C., Ugur, M.S. et al. The relationship between FDI, CO2 emissions, and energy consumption in Asia-Pacific economic cooperation countries. Environ Sci Pollut Res 30, 42845–42862 (2023). https://doi.org/10.1007/s11356-021-17494-3

Baloch MA, Zhang J, Iqbal K, Iqbal Z (2019) The effect of financial development on ecological footprint in BRI countries: evidence from panel data estimation. Environ Sci Pollut Res 26:6199–6208

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., & Farhani, S. (2018). How economic growth, renewable electricity, and natural resources contribute to CO2 emissions? Energy Policy, 113, 356–367.

Begum, R. A., Sohag, K., Abdullah, S. M. S., & Jaafar, M. (2015). CO2 emissions, energy consumption, economic and population growth in Malaysia. Renewable and Sustainable Energy Reviews, 41, 594-601. https://doi.org/10.1016/j.rser.2014.07.205

Boubacar, S., Sarpong, F.A. & Nyantakyi, G. Shades of sustainability: decoding the impact of foreign direct investment on CO2 emissions in Africa's growth trajectory. Environ Dev Sustain (2024). https://doi.org/10.1007/s10668-024-04656-9

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. Econometrica: Journal of the econometric society, 1287-1294. https://doi.org/10.2307/1911963

British Petroleum (2022). Energy Data. https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/downloads.html, Accessed 31 July 2022

Chen P, Gao J, Ji Z et al (2022) Do artificial intelligence applications affect carbon emission performance?—Evidence from panel data analysis of Chinese cities. Energies 15(15):5730. https://doi.org/10.3390/en15155730

Chen, P., Gao, J., Ji, Z., Liang, H., & Peng, Y. (2022). Do artificial intelligence applications affect carbon emission performance?—evidence from panel data analysis of Chinese cities. Energies, 15(15), 5730. https://doi.org/10.3390/en15155730

Chien, F., Hsu, C. C., Zhang, Y., & Sadiq, M. (2023). Sustainable assessment and analysis of energy consumption impact on carbon emission in G7 economies: mediating role of foreign direct investment. Sustainable Energy Technologies and Assessments, 57, 103111. https://doi.org/10.1016/j.seta.2023.103111

Dehdar, F., Fuinhas, J.A., Karimi Alavijeh, N. et al. Investigating the determinants of carbon emissions in the USA: a state-level analysis. Environ Sci Pollut Res 30, 23023–23034 (2023). https://doi.org/10.1007/s11356-022-23831-x

Delanoë, P., Tchuente, D., & Colin, G. (2023). Method and evaluations of the effective gain of artificial intelligence models for reducing CO2 emissions. Journal of environmental management, 331, 117261. https://doi.org/10.1016/j.jenvman.2023.117261

Dicky DA, Fuller WA (1979) Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 74:427–431

Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. Human ecology review, 1(2), 277-300. https://www.jstor.org/stable/24706840

Dietz, T., & Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. Proceedings of the National Academy of Sciences, 94(1), 175-179. https://doi.org/10.1073/pnas.94.1.175

Dogan, E., Turkekul, B. CO2 emissions, real output, energy consumption, trade, urbanization and financial development: testing the EKC hypothesis for the USA. Environ Sci Pollut Res 23, 1203–1213 (2016). https://doi.org/10.1007/s11356-015-5323-8

Dong, M., Wang, G. & Han, X. Artificial intelligence, industrial structure optimization, and CO2 emissions. Environ Sci Pollut Res 30, 108757–108773 (2023). https://doi.org/10.1007/s11356-023-29859-x

Duan Y, Jiang X (2021) Pollution haven or pollution halo? A re-evaluation on the role of multinational enterprises in global CO2 emissions. Energy Econ 97:105181

Ehrlich, P. R., & Holdren, J. P. (1971). Impact of Population Growth: Complacency concerning this component of man's predicament is unjustified and counterproductive. Science, 171(3977), 1212-1217. https://doi.org/10.1126/science.171.3977.1212

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1992). Efficient tests for an autoregressive unit root.

Esquivias, M.A., Sugiharti, L., Rohmawati, H., Rojas, O., Sethi, N., 2022. Nexus between technological innovation, renewable energy, and human capital on the environmental sustainability in emerging Asian economies: a panel quantile regression approach. Energies 15 (7), 2451. http://dx.doi.org/10. 3390/en15072451.

Fuller, W. A. (2009). Introduction to statistical time series. John Wiley & Sons.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. Econometrica: journal of the Econometric Society, 424-438. https://doi.org/10.2307/1912791

Grigg, D. (1991). World Agriculture: Productivity and Sustainability, Ch. 2. Environment, Population and Development. Hodder and Stoughton in Association with the Open University.

Harris, B. (2020). The Biden plan for a clean energy revolution and environmental justice. Biden Harris.

Herrerias, M. J., Cuadros, A., & Luo, D. (2016). Foreign versus indigenous innovation and energy intensity: Further research across Chinese regions. Applied Energy, 162, 1374–1384. https://doi.org/10.1016/j.apenergy.2015.01.042

Jarque, C. M., & Bera, A. K. (1987). A test for normality of observations and regression residuals. International Statistical Review/Revue Internationale de Statistique, 163-172. https://doi.org/10.2307/1403192.

Jiang W, Gong SH, Li XT et al (2022) Robot shock, capital-embodied technological progress and carbon reduction of manufacturing sector——theoretical analysis and empirical evidence from China. China Ind Econ (10):24–42. https://doi.org/10.13653/j.cnki.jqte.2022.12.008

Kartal, M. T., Samour, A., Adebayo, T. S., & Depren, S. K. (2023). Do nuclear energy and renewable energy surge environmental quality in the United States? New insights from novel bootstrap Fourier Granger causality in quantiles approach. Progress in Nuclear Energy, 155, 104509.

Khalid, T., Wen, J., Khalid, M., Khalid, S., Zakaria, M., & Mahmood, H. (2023). Does Technological Innovation Reduce Environmental Degradation? Evidence from China. Engineering Economics, 34(3), 323-334.

Kihombo S, Ahmed Z, Chen S, Adebayo TS, Kirikkaleli D (2021) Linking financial development, economic growth, and ecological footprint: what is the role of technological innovation? Environ Sci Pollut Res 28:61235–61245 https://doi.org/10.1007/s11356-021-14993-1

Kouassi, V. D., Xu, H., Bosah, C. P., Ayimadu, T. E., & Nadege, M. N. (2024). Sustainable Energy Usage for Africa: The Role of Foreign Direct Investment in Green Growth Practices to Mitigate CO2 Emissions. Energies, 17(15), 3847. https://doi.org/10.3390/en17153847

Lahiani A (2020) Is financial development good for the environment? An asymmetric analysis with CO2 emissions in China. Environ Sci Pollut Res 27:7901–790

Latif, N., & Faridi, M. Z. (2023). Examining the impact of financial development on load capacity factor (LCF): System GMM analysis for Asian economies. Frontiers in Energy Research, 10, 1063212.

Liu, J., Liu, L., Qian, Y., & Song, S. (2022). The effect of artificial intelligence on carbon intensity: evidence from China's industrial sector. Socio-Economic Planning Sciences, 83, 101002. https://doi.org/10.1016/j.seps.2020.101002

Mehmood U, Tariq S (2020) Globalization and CO2 emissions nexus: evidence from the EKC hypothesis in South Asian countries. Environ Sci Pollut Res 27:1–13. https://doi.org/10.1007/s11356-020-09774-1

Mehmood, U. Analyzing the Role of Political Risk, GDP, and Eco-Innovations Towards CO2 Emissions in South Asian Countries. J Knowl Econ 15, 2121–2135 (2024). https://doi.org/10.1007/s13132-023-01292-y

Mehmood, U., Tariq, S., Ul-Haq, Z. et al. Does the modifying role of institutional quality remains homogeneous in GDP-CO2 emission nexus? New evidence from ARDL approach. Environ Sci Pollut Res 28, 10167–10174 (2021). https://doi.org/10.1007/s11356-020-11293-y

Nassef, A. M., Olabi, A. G., Rezk, H., & Abdelkareem, M. A. (2023). Application of artificial intelligence to predict CO2 emissions: critical step towards sustainable environment. Sustainability, 15(9), 7648. https://doi.org/10.3390/su15097648

Ozturk I, Al-Mulali U (2015) Investigating the validity of the environmental Kuznets curve hypothesis in Cambodia. Ecol Indic 57:324 330. https://doi.org/10.1016/j.ecolind.2015.05.018

Pachiyappan, D., Ansari, Y., Alam, M. S., Thoudam, P., Alagirisamy, K., & Manigandan, P. (2021). Short and long-run causal effects of CO2 emissions, energy use, GDP and population growth: evidence from India using the ARDL and VECM approaches. Energies, 14(24), 8333. https://doi.org/10.3390/en14248333

Park JY (1992) Canonical cointegrating regressions. Econometrica 60:119–143. https://doi.org/10.2307/2951679

Pata, U. K., Kartal, M. T., Adebayo, T. S., & Ullah, S. (2023). Enhancing environmental quality in the United States by linking biomass energy consumption and load capacity factor. Geoscience Frontiers, 14(3), 101531.

Pattak, D. C., Tahrim, F., Salehi, M., Voumik, L. C., Akter, S., Ridwan, M., ... & Zimon, G. (2023). The driving factors of Italy's CO2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. Energies, 16(15), 5845. https://doi.org/10.3390/en16155845

Peng, J. J. (2019). Factors Affecting Carbon Emissions in the Construction Industry based on STIRPAT Model: Taking Henan Province of China as an Example. Nature Environment & Pollution Technology, 18(3).

Pesaran, M. H., & Timmermann, A. (2005). Small sample properties of forecasts from autoregressive models under structural breaks. Journal of Econometrics, 129(1-2), 183-217.

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.

Phillips PB, Perron P (1988) Testing for a unit root in time series regression. Biometrika 75:335–346

Phillips PCB, Hansen BE (1990) Statistical inference in instrumental variables regression with I (1) processes. Rev Econ Stud 57:99–125. https://doi.org/10.2307/2297545

Pradhan, K.C., Mishra, B. & Mohapatra, S.M. Investigating the relationship between economic growth, energy consumption, and carbon dioxide (CO2) emissions: a comparative analysis of South Asian nations and G-7 countries. Clean Techn Environ Policy (2024). https://doi.org/10.1007/s10098-024-02802-5

Raihan A, Tuspekova A (2023) Towards net zero emissions by 2050: the role of renewable energy, technological innovations, and forests in New Zealand. JESCAE 2:1–16. https://doi.org/10.56556/jescae.v2i1.422

Raihan, A., Atasoy, F. G., Atasoy, M., Ridwan, M., & Paul, A. (2022b). The role of green energy, globalization, urbanization, and economic growth toward environmental sustainability in the United States. Journal of Environmental and Energy Economics, 1(2), 8-17. https://doi.org/10.56946/jeee.v1i2.377

Raihan, A., Bala, S., Akther, A., Ridwan, M., Eleais, M., & Chakma, P. (2024c). Advancing environmental sustainability in the G-7: The impact of the digital economy, technological innovation, and financial accessibility using panel ARDL approach. Journal of Economy and Technology. https://doi.org/10.1016/j.ject.2024.06.001

Raihan, A., Hasan, M. A., Voumik, L. C., Pattak, D. C., Akter, S., & Ridwan, M. (2024b). Sustainability in Vietnam: Examining Economic Growth, Energy, Innovation, Agriculture, and Forests' Impact on CO2 Emissions. World Development Sustainability, 100164. https://doi.org/10.1016/j.wds.2024.100164

Raihan, A., Ridwan, M., Tanchangya, T., Rahman, J., & Ahmad, S. (2023a). Environmental Effects of China's Nuclear Energy within the Framework of Environmental Kuznets Curve and Pollution Haven Hypothesis. Journal of Environmental and Energy Economics, 2(1), 1-12. https://doi.org/10.56946/jeee.v2i1.346

Raihan, A., Tanchangya, T., Rahman, J., & Ridwan, M. (2024a). The Influence of Agriculture, Renewable Energy, International Trade, and Economic Growth on India's Environmental Sustainability. Journal of Environmental and Energy Economics, 37-53. https://doi.org/10.56946/jeee.v3i1.324

Raihan, A., Tanchangya, T., Rahman, J., Ridwan, M., & Ahmad, S. (2022a). The influence of Information and Communication Technologies, Renewable Energies and Urbanization toward Environmental Sustainability in China. Journal of Environmental and Energy Economics, 1(1), 11-23. https://doi.org/10.56946/jeee.v1i1.351

Raihan, A., Voumik, L. C., Ridwan, M., Ridzuan, A. R., Jaaffar, A. H., & Yusoff, N. Y. M. (2023b). From growth to green: navigating the complexities of economic development, energy sources, health spending, and carbon emissions in Malaysia. Energy Reports, 10, 4318-4331. https://doi.org/10.1016/j.egyr.2023.10.084

Raihan, A., Voumik, L.C., Rahman, M.H. et al. Unraveling the interplay between globalization, financial development, economic growth, greenhouse gases, human capital, and renewable energy uptake in Indonesia: multiple econometric approaches. Environ Sci Pollut Res 30, 119117–119133 (2023b). https://doi.org/10.1007/s11356-023-30552-2

Rehman, A., Alam, M.M., Ozturk, I. et al. Globalization and renewable energy use: how are they contributing to upsurge the CO2 emissions? A global perspective. Environ Sci Pollut Res 30, 9699–9712 (2023). https://doi.org/10.1007/s11356-022-22775-6

Rehman, A., Ma, H., Ozturk, I. et al. Sustainable development and pollution: the effects of CO2 emission on population growth, food production, economic development, and energy consumption in Pakistan. Environ Sci Pollut Res 29, 17319–17330 (2022). https://doi.org/10.1007/s11356-021-16998-2

Ridwan, M., Raihan, A., Ahmad, S., Karmakar, S., & Paul, P. (2023). Environmental sustainability in France: The role of alternative and nuclear energy, natural resources, and government spending. Journal of Environmental and Energy Economics, 2(2), 1-16.https://doi.org/10.56946/jeee.v2i2.343

Ridwan, M., Urbee, A. J., Voumik, L. C., Das, M. K., Rashid, M., & Esquivias, M. A. Research in Globalization. https://doi.org/10.1016/j.resglo.2024.100223

Rjoub, H., Odugbesan, J. A., Adebayo, T. S., & Wong, W.-K. (2021). Sustainability of the moderating role of financial development in the determinants of environmental degradation: Evidence from Turkey. Sustainability, 13(4), 1844. https://doi.org/10.3390/SU13041844

Saadaoui, H., Dogan, M. & Omri, E. The impacts of hydroelectricity generation, financial development, geopolitical risk, income, and foreign direct investment on carbon emissions in Turkey. Environ Econ Policy Stud 26, 239–261 (2024). https://doi.org/10.1007/s10018-023-00384-y

Salahuddin, M., Alam, K., Ozturk, I., & Sohag, K. (2018). The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO2 emissions in Kuwait. Renewable and sustainable energy reviews, 81, 2002-2010. https://doi.org/10.1016/j.rser.2017.06.009

Sapkota P, Bastola U (2017) Foreign direct investment, income, and environmental pollution in developing countries: panel data analysis of Latin America. Energy Econ 64:206–212

Saud, S., Chen, S., and Haseeb, A. (2018). Impact of financial development and economic growth on environmental quality: An empirical analysis from belt and road initiative (BRI) countries. Environ. Sci. Pollut. Res. 17, 2253–2269. doi:10.1007/s11356-018-3688-1

Shahbaz, M., Dogan, M., Akkus, H.T. et al. The effect of financial development and economic growth on ecological footprint: evidence from top 10 emitter countries. Environ Sci Pollut Res 30, 73518–73533 (2023). https://doi.org/10.1007/s11356-023-27573-2

Shahbaz, M., Gozgor, G., Adom, P. K., & Hammoudeh, S. (2019). The technical decomposition of carbon emissions and the concerns about FDI and trade openness effects in the United States. International Economics, 159, 56-73. https://doi.org/10.1016/j.inteco.2019.05.001

Shahbaz, M., Raghutla, C., Song, M., Zameer, H., & Jiao, Z. (2020). Public-private partnerships investment in energy as new determinant of CO2 emissions: the role of technological innovations in China. Energy Economics, 86, 104664.

Shoaib HM, Rafique MZ, Nadeem AM, Huang S (2020) Impact of financial development on CO2 emissions: a comparative analysis of developing countries (D8) and developed countries (G8). Environ Sci Pollut Res 27:12461–12475

Shu, X., Usman, M., Ahmad, P., & Irfan, M. (2024). Analyzing the asymmetric FinTech services under natural resources, and renewable energy in the future environmental performance: New insights from STIRPAT model framework. Resources Policy, 92, 104984. https://doi.org/10.1016/j.resourpol.2024.104984

Stock JH, Watson MW (1993) A simple estimator of cointegrating vectors in higher-order integrated systems. Econometrica 61:783–820. https://doi.org/10.2307/2951763

Suhrab, M., Soomro, J.A., Ullah, S. et al. The effect of gross domestic product, urbanization, trade openness, financial development, and renewable energy on CO2 emission. Environ Sci Pollut Res 30, 22985–22991 (2023). https://doi.org/10.1007/s11356-022-23761-8

Sulaiman, C., & Abdul-Rahim, A. S. (2018). Population growth and CO2 emission in Nigeria: a recursive ARDL approach. Sage Open, 8(2), 2158244018765916. https://doi.org/10.1177/2158244018765916

Sultana, T., Hossain, M. S., Voumik, L. C., & Raihan, A. (2023). Energy Reports. https://doi.org/10.1016/j.egyr.2023.06.020

Tamazian, A., & Rao, B. B. (2010). Do economic, financial and institutional developments matter for environmental degradation? Evidence from transitional economies. Energy economics, 32(1), 137-145. https://doi.org/10.1016/j.eneco.2009.04.004

U.S. Energy Information Administration, 2019, International Energy Outlook, https://www.eia.gov/outlooks/ieo/pdf/ieo2019.pdf, Accessed November 7, 2020.

U.S. EPA, Sources of Greenhouse Gas Emissions. https://www.epa.gov/ ghgemissions/sources-greenhouse-gas-emissions#carbon-dioxide, Accessed November 7, 2020

Udemba, E.N., Magazzino, C. & Bekun, F.V. Modeling the nexus between pollutant emission, energy consumption, foreign direct investment, and economic growth: new insights from China. Environ Sci Pollut Res 27, 17831–17842 (2020). https://doi.org/10.1007/s11356-020-08180-x

Ulussever, T., Kılıç Depren, S., Kartal, M.T. et al. Estimation performance comparison of machine learning approaches and time series econometric models: evidence from the effect of sector-based energy consumption on CO2 emissions in the USA. Environ Sci Pollut Res 30, 52576–52592 (2023). https://doi.org/10.1007/s11356-023-26050-0

UN. 2017. The Emissions Gap Report 2017, a UN environment synthesis report. United Nations Environment Programme. November. Available at: https://digitallibrary.un. org/record/3894804.

Voumik, L. C., & Ridwan, M. (2023). Impact of FDI, industrialization, and education on the environment in Argentina: ARDL approach. Heliyon, 9(1). https://doi.org/10.1016/j.heliyon.2023.e12872

Voumik, L. C., Ghosh, S., Rashid, M., Das, M. K., Esquivias, M. A., & Rojas, O. (2024). The effect of geopolitical risk and green technology on load capacity factors in BRICS. Utilities Policy, 88, 101757. https://doi.org/10.1016/j.jup.2024.101757

Voumik, L. C., Rahman, M. H., Rahman, M. M., Ridwan, M., Akter, S., & Raihan, A. (2023). Toward a sustainable future: Examining the interconnectedness among Foreign Direct Investment (FDI), urbanization, trade openness, economic growth, and energy usage in Australia. Regional Sustainability, 4(4), 405-415. https://doi.org/10.1016/j.regsus.2023.11.003

Voumik, L. C., Ridwan, M., Rahman, M. H., & Raihan, A. (2023). An investigation into the primary causes of carbon dioxide releases in Kenya: Does renewable energy matter to reduce carbon emission?. Renewable Energy Focus, 47, 100491.https://doi.org/10.1016/j.ref.2023.100491

Wan Mohd Jaafar, W. S., Abdul Maulud, K. N., Muhmad Kamarulzaman, A. M., Raihan, A., Md Sah, S., Ahmad, A., ... & Razzaq Khan, W. (2020). The influence of deforestation on land surface temperature—A case study of Perak and Kedah, Malaysia. Forests, 11(6), 670. https://doi.org/10.3390/f11060670

Wang, Q., Jiang, X. T., Ge, S., & Jiang, R. (2019). Is economic growth compatible with a reduction in CO2 emissions? Empirical analysis of the United States. Resources, Conservation and Recycling, 151, 104443. https://doi.org/10.1016/j.resconrec.2019.104443

Wang, Q., Zhang, F., Li, R., & Sun, J. (2024). Does artificial intelligence promote energy transition and curb carbon emissions? The role of trade openness. Journal of Cleaner Production, 447, 141298. https://doi.org/10.1016/j.jclepro.2024.141298

Wei D, Chen Z, Rose A (2019) Estimating economic impacts of the US-South Korea free trade agreement. Econ Syst Res 31(3):305–323. https://doi.org/10.1080/09535314.2018.1506980Return to ref 2019 in article

World Bank (2022) GDP Current US$. https://data.worldbank.org, Accessed 16 May 2022

Yang B, Usman M, Jahanger A (2021) Do industrialization, economic growth and globalization processes influence the ecological footprint and healthcare expenditures? Fresh insights based on the STIRPAT model for countries with the highest healthcare expenditures. Sustain Prod Consum 28:893–910. https://doi.org/10.1016/j.spc.2021.07.020

Yang L, Hui P, Yasmeen R, Ullah S, Hafeez M (2020) Energy consumption and financial development indicators nexuses in Asian economies: a dynamic seemingly unrelated regression approach. Environ Sci Pollut Res 27(14):16472–1648.

Yao X, Yasmeen R, Hussain J, Shah WUH (2021) The repercussions of financial development and corruption on energy efficiency and ecological footprint: evidence from BRICS and next 11 countries. Energy 223:120063

Yu, X., Kuruppuarachchi, D., & Kumarasinghe, S. (2024). Financial development, FDI, and CO2 emissions: does carbon pricing matter?. Applied Economics, 56(25), 2959-2974. https://doi.org/10.1080/00036846.2023.2203460

Zafar MW, Saud S, Hou F (2019) The impact of globalization and financial development on environmental quality: evidence from selected countries in the Organization for Economic Co-operation and Development (OECD). Environ Sci Pollut Res 26(13):13246–13262

Zafar, M. W., Saleem, M. M., Destek, M. A., & Caglar, A. E. (2022). The dynamic linkage between remittances, export diversification, education, renewable energy consumption, economic growth, and CO2 emissions in top remittance-receiving countries. Sustainable Development, 30(1), 165-175.

Zafar, M. W., Zaidi, S. A. H., Khan, N. R., Mirza, F. M., Hou, F., & Kirmani, S. A. A. (2019). The impact of natural resources, human capital, and foreign direct investment on the ecological footprint: the case of the United States. Resources Policy, 63, 101428. https://doi.org/10.1016/j.resourpol.2019.101428

Zhang Z, Nuță FM, Dimen L et al (2023) Relationship between FDI inflow, CO2 emissions, renewable energy consumption, and population health quality in China. Front Environ Sci 11:1120970. https://doi.org/10.3389/fenvs.2023.1120970

Zhang, C., & Zhou, X. (2016). Does foreign direct investment lead to lower CO2 emissions? Evidence from a regional analysis in China. Renewable and Sustainable Energy Reviews, 58, 943-951. https://doi.org/10.1016/j.rser.2015.12.226

Zhang, S., Liu, J. & Liu, X. Comparing the environmental impacts of nuclear and renewable energy in top 10 nuclear-generating countries: evidence from STIRPAT model. Environ Sci Pollut Res 30, 31791–31805 (2023). https://doi.org/10.1007/s11356-022-24438-y

Zhao, ., Gao, Y. & Sun, X. The impact of artificial intelligence on pollution emission intensity—evidence from China. Environ Sci Pollut Res 30, 91173–91188 (2023). https://doi.org/10.1007/s11356-023-28866-2

Zhu, H., Duan, L., Guo, Y., & Yu, K. (2016). The effects of FDI, economic growth and energy consumption on carbon emissions in ASEAN-5: evidence from panel quantile regression. Economic Modelling, 58, 237-248.