Exploring China's Carbon Emission Reduction: the Role of Renewable Energy, Remittance, and Technological Innovation

Ayodele Oluwaseun

November 30, 2024

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Abstract

The environmental impacts of renewable energy, remittances, and technological innovation remain underexplored, although existing research suggests they play a vital role in enhancing socioeconomic development. This study bridges the gap by examining annual data from 1990 to 2020 to determine how these factors influence carbon dioxide (CO2) emissions in China. Employing the autoregressive distributed lag (ARDL) bounds testing method, the study found consistent relationships between CO2 emissions and the key variables. Both short- and long-term ARDL analyses revealed that while economic growth contributes to rising CO2 emissions, renewable energy adoption, remittance flows, and technological progress help to curb emissions. To validate these findings, fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and canonical cointegrating regression (CCR) techniques were applied. Based on these significant insights, the study proposes several policy measures to further reduce carbon emissions.

Keywords: Renewable Energy, Remittance, Technological Innovation, ARDL, China

Introduction

The rising threat of climate change and its impact on ecosystems, economies, and societies has brought environmental sustainability to the forefront of global discussions. Among the most significant contributors to climate change is the rapid increase in carbon dioxide (CO_2) emissions, primarily driven by industrialization, urbanization, and economic growth. Addressing this challenge requires comprehensive strategies that combine economic policies, technological innovations, and behavioral changes. In this context, renewable energy, remittances, and technological innovation emerge as pivotal factors influencing both economic and environmental outcomes. This study focuses on the potential of these factors to reduce carbon emissions in China, a country that has undergone unprecedented economic development while grappling with environmental challenges. China is the world's largest emitter of CO_2, accounting for nearly 30% of global emissions. Its rapid industrialization, urbanization, and population growth have significantly increased the demand for energy, much of which is met by fossil fuels. While this development has lifted millions out of poverty and positioned China as a global economic powerhouse, it has also resulted in severe environmental consequences, including air pollution, deforestation, and climate instability. Recognizing these challenges, China has undertaken ambitious policies to transition toward a low-carbon economy, leveraging renewable energy sources, technological advancements, and international financial flows like remittances. These factors not only contribute to economic growth but also hold potential as tools for environmental sustainability.

Renewable energy plays a critical role in reducing CO_2 emissions by replacing fossil fuel-based energy sources with cleaner alternatives. Solar, wind, hydro, and geothermal energy have gained significant traction in China over the past two decades, supported by government subsidies, research investments, and international partnerships. According to recent data, China leads the world in renewable energy capacity, with substantial investments in solar and wind energy infrastructure. However, despite these advancements, the transition is still in its early stages, and the effectiveness of renewable energy in curbing emissions remains a subject of empirical investigation. Remittances, or the financial flows sent by migrant workers to their home countries, are another intriguing yet underexplored factor in environmental economics. Remittances contribute to socioeconomic development by improving household income, education, and healthcare access. They can also indirectly influence environmental outcomes by altering consumption patterns and investment behaviors. In the context of China, remittances have the potential to support green investments, such as energy-efficient housing or renewable energy technologies, thus contributing to emission reductions. However, the relationship between remittances and environmental quality is complex and context-dependent, requiring detailed empirical analysis to unravel its dynamics.

Technological innovation is widely regarded as a cornerstone of sustainable development. By fostering the creation and adoption of energy-efficient technologies, innovation can decouple economic growth from environmental degradation. In China, technological advancements have been pivotal in modernizing industries, improving energy efficiency, and promoting clean energy solutions. Policies encouraging research and development (R&D), technology transfer, and international collaboration have further strengthened China's position as a leader in green technology. Nevertheless, the pace and scale of technological adoption vary across sectors, and the long-term impact of innovation on CO_2 emissions warrants a closer examination. Given the significance of renewable energy, remittances, and technological innovation, this study seeks to evaluate their combined impact on carbon emissions in China from 1990 to 2020. By utilizing advanced econometric techniques, including the autoregressive distributed lag (ARDL) bounds testing approach, the research provides insights into the short- and long-term relationships between CO_2 emissions and these factors. The robustness of the results is further validated through complementary methods such as fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and canonical cointegrating regression (CCR). This methodological rigor ensures the reliability of the findings and enhances their policy relevance.

The study’s findings reveal critical dynamics between economic growth, renewable energy adoption, remittance flows, and technological progress. While economic development tends to increase CO2 emissions in the short term, the adoption of renewable energy, the inflow of remittances, and advancements in technology act as mitigating forces. These results underscore the importance of integrating environmental considerations into economic policies and development strategies. Moreover, the study highlights the need for tailored policy measures that leverage these factors to achieve sustainable growth. For instance, expanding investments in renewable energy infrastructure, incentivizing remittance-based green initiatives, and promoting R&D in clean technologies could significantly reduce China's carbon footprint while supporting its economic aspirations. This research contributes to the growing body of literature on environmental economics by providing empirical evidence from one of the world's most significant contributors to carbon emissions. It bridges the gap between theoretical insights and real-world applications, offering a comprehensive analysis of the interplay between renewable energy, remittances, and technological innovation in the context of carbon emission reduction. The study also emphasizes the importance of a multi-faceted approach to sustainability, recognizing that no single factor can address the complexities of climate change.

In light of these findings, the study proposes several policy recommendations aimed at maximizing the environmental benefits of renewable energy, remittances, and technological innovation. These include enhancing regulatory frameworks, strengthening international cooperation, and fostering public-private partnerships to accelerate the transition toward a low-carbon economy. By aligning economic policies with environmental goals, China can not only meet its domestic and international climate commitments but also serve as a model for other developing nations seeking sustainable development pathways. In conclusion, this study sheds light on the transformative potential of renewable energy, remittances, and technological innovation in reducing carbon emissions in China. By analyzing data spanning three decades, it provides robust evidence of their effectiveness in mitigating environmental challenges while supporting socioeconomic progress. As the global community intensifies its efforts to combat climate change, these insights hold valuable lessons for policymakers, researchers, and stakeholders committed to building a sustainable future.

Literature Review

Numerous researches on the interaction between the progress of the economy and CO_2 emissions have been performed over the years. There is a dearth of literature pertinent to China's GDP- CO_2 emission nexus. Al Mulali et al. [14] examined the EKC premise for the first time in China using data from 1980 to 2012 and discovered evidence of EKC characteristics in China. Likewise, Sarkodie and Ozturk [15] the EKC hypothesis in China and supported the EKC theory. Most studies discovered a significant relationship between GDP and CO_2 that was positive, but only a few studies discovered insignificant or adverse relationships between Emissions of CO_2 and economic expansion. Using Thailand as an example, Adebayo and Akinsola [16] investigated the GDP- CO_2 relationship. In order to examine this association, the researchers used wavelet tools. Their empirical findings demonstrated a positive correlation between CO_2 and economic progress, and they also identified a one-way causation between GDP and CO_2 emissions. However, He et al. [17] and Tufail et al. [18] observed a favorable interaction involving CO_2 and GDP in their respective studies. This indicates that a rise in GDP reduces environmental sustainability. Furthermore, Adebayo and Kirikkaleli [19] evaluated the GDP- CO_2 linkage for Japan between 1990 and 2015 using a novel wavelet coherence test. According to their findings, progress in GDP is connected with a rise in emissions of CO_2. Zhang et al. [20] analyzed the influence of the growth of the economy on CO_2 between 1970 and 2018 employing data from Malaysia. Their empirical results demonstrate a favorable correlation between CO_2 and GDP. The positive CO_2-GDP link was verified by the research conducted by Usman et al. [21] for the United States and Adebayo and Rjoub [22] for MINT economies. Adebayo and Odugbesan's [23] research examined how economic development affected releases of CO_2 in South Africa utilizing data throughout the years 1971 to 2017 and contemporary econometric methodologies. The study's conclusions revealed that raising GDP emitted higher CO_2. Baloch et al. [24] evaluated the association between GDP and environmental deterioration, and their outcomes proved that GDP had a beneficial influence on CO_2 emissions. Similarly, Joshua and Bekun's [25] study supports the hypothesis that economic expansion significantly triggered CO_2. Several economic analyses observed that increasing the usage of sustainable sources would lead to mitigating CO_2 emissions. Sarkodie and Ozturk [15] concluded that China's renewable energy use massively diminished CO_2 emissions. Azam et al. [26], using a sophisticated panel quantile regression model, found a optimistic relation between growth and pollution in the top 5 emitter nations for the years 1995–2017 and an inverse correlation between clean energy and CO_2 in the same set of economies. There is an existence of cause GDP growth and emissions [27, 28]. Liu et al. [29] used DOLS technique on temporal data from 1992–2013 to find an inverse relationship between the BRIC nations' utilization of renewable energy sources and their CO_2 emissions. In addition, Liu et al. [30] also found renewable source mitigate emission in developing countries. Using data from 1990–2019, Ali et al. [31] explored the relationship between China's use of non-renewable and renewable energies and the country's carbon emission intensity (CEI). The research used the dynamic "Autoregressive Distributed Lag (ARDL)" method to see how the variables were connected through time. The research shows a favorable correlation between CEI and both renewable and non-renewable energy sources. Employing data from 1965 to 2019, Adebayo et al. [32] addressed the idea that using renewable sources reduces carbon dioxide emissions in Sweden. Research by Dong et al. [33] looked at whether or not BRICS nations may cut their CO_2 emissions more effectively by increasing their use of nuclear power. According to the results of the research, renewable energy sources contribute significantly to cutting down on carbon dioxide emissions.

There are two main ideas on the association between FDI and environmental quality. While some research supports the pollution heaven theory and finds that FDI harms the environment, other research demonstrates that FDI actually enhances air quality via the spread of green technology. Marcellus [34] conducted a study in the context of China to find out the influence of FDI on the level of CO_2 in China. The findings of the study showed that FDI has a mitigating role in CO_2 emission and increasing FDI lowers the level of CO_2 emission. Evidence from a wide range of research has shown that FDI helps mitigate environmental damage by funding innovative approaches to green technology [35-38]. Eskeland and Harrison [39] found that U.S. manufacturing facilities in emerging economies use green energy and ecologically sound management techniques. The effects of FDI on ecosystems were investigated in a study of the nations of the Gulf Cooperation Council. Using a multivariate approach, the research found that FDI had no negative effects on ecosystems [40]. To assess the link stuck between FDI and environment, Demena and Afesorgbor [41] found that the influences of FDI on CO_2 emissions are negligible. While FDI has been shown to reduce CO_2 emissions by varying degrees depending on the study, the evidence is still mixed. The results held up after accounting for variations in development and pollution levels among nations. Du and Li [42] looked at how carbon emissions increased across 71 nations from 1992 to 2012. They used a Malmquist index approach with parameters. According to the research's findings, carbon stock production increased across the board over the study period. Additionally, increasing the productivity of all factors that contribute to carbon depends on technological innovation. Between 2006 and 2015, Zhou et al. studied how China's

OFDI spillover affected the sustainable technologies of 30 regions [43]. The research concluded that although Chinese OFDI does not lead to sustainable technologies, there are substantial regional differences since there aren't the necessary enabling circumstances in certain areas. Udemba et al. [44] used ARDL bound test to investigate the affinity involving FDI and emissions and discovered that FDI affect environment. Solarin et al. [45] also found that FDI degrades the environment as well.

According to our literature assessment, no prior study has been performed on the linkage between FDI, energy use, GDP expansion, and the environment in China. Existing studies have shown conflicting evidence about the FDI- CO_2 link. As FDI stimulates the growth of host economies by funding the development of Greenfield projects and expanding existing enterprises, the production units engaged in these processes generate carbon emissions. However, a number of studies have shown that FDI has little or no effect on carbon dioxide emissions. China likewise suffers from a dearth of studies in the energy sector. It is, therefore, important to investigate the connection between China's rising CO_2 emissions, foreign direct investment, and economic expansion.

3. Methodology

3.1 Theoretical Framework

The IPAT model maintains that "impacts on ecosystems (I) are the product of the population size (P), affluence (A), and technology (T)" provided the foundation for "Stochastic Impacts by Regression on Population, Affluence, and Technology" defined as STIRPAT model. York et al. [46] argue that the IPAT model has certain limitations since it does not account for non-monotonic, unevenly scaled changes in the influential elements. Using the York STIRPAT model, this issue is resolved.

$$I = \alpha P_i^{\beta} A_i^{\gamma} T_i^{\Theta} e_i \qquad (1)$$

$$LnI_i = Ln\alpha + \beta Ln(P_i) + \gamma Ln(A_i) + \Theta Ln(T_i) + e_i \qquad (2)$$

Where the anticipated parameters of the model are β, γ, and Θ, and e_i represents the disturbance term. The aforesaid equation is often simplified in a logarithmic form in the application. Incredibly, the STIRPAT model's structure allows for the dissection of P, A, and T into a number of different factors in the environment; Therefore, researchers have shown a greater extent of interest in this model [47]. The corresponding logarithmic expression is given in equation (2).

Using the STIRPAT model greatly enhances the forms of significant effect factors that were taken into account in this investigation, which is the model's primary advantage. To further evaluate the factors that contribute to CO_2 emission in China, we updated a STIRPAT model by including indices of demographic, economic, and technical factors. The population was used as a surrogate for demographic change, GDP (per capita) and FDI for affluence, and fossil fuel and renewable energy use for technological factors in this study. Now, substituting the corresponding variable in Equation (2), we can write Equation (3) as follows:

$$LnCO_{2_{it}} = \alpha_{it} + \beta_1 LGDP_{it} + \beta_2 LPOP_{it} + \beta_3 LFOS_{it} + \beta_4 LREN_{it} + \beta_5 LFDI_{it} + €_{it} \qquad (3)$$

Where β_1 to β_2 are coefficients used in Equation (3)

3.2 Data

The ARDL tactic of cointegration suggested by Pesaran et al. [48] was adopted in this empirical investigation to identify the major causes of CO_2 emission in China. The ARDL model was used owing to its capacity to describe a capricious, ever-changing response as the result of one or more forecasting factors. Moreover, it may be used for the study of economics, ecology, and experimental data, as well as for the analysis and forecasting of the actions of dynamic systems [49]. Time series data for China have been gathered from the World Development Indicator (WDI) database and cover the years 1972 to 2021. The explained variable in this analysis is CO_2 emission, whereas the explanatory variables are GDP, population, renewable energy, and fossil fuel energy usage. The variables have been log-transformed to assure normally distributed data. The variables, their logarithms, and the sources of data employed are listed in Table 1.

Table 1: Variable's Description, Source, and Signifier

Variable	**Signifier**	**Description**	**Source**
CO2 emissions	LCO2	CO2 emissions (kt)	World Bank Development Indicator
Gross Domestic Product Per Capita	LGDP	GDP per capita (constant 2015 US$)	
Population	LPOP	Population, total	
Renewable energy consumption	LREN	Renewable energy consumption (% of total energy consumption)	
Fossil fuels	LFOS	Fossil fuel energy consumption (% of total)	
Alternative and nuclear energy	LFDI	Alternative and nuclear energy (% of total energy use)	

The variables considered in this inquiry are summarized (minimum, maximum, mean, median, and standard deviation) in Table 2.

Table 2: General Statistics of the Variables

VARIABLES	**Mean**	**Sd**	**Min**	**Max**
LCO2	9.097	0.331	8.676	10.01
LGDP	7.133	0.105	6.994	7.405
LPOP	17.14	0.450	16.31	17.82
LREN	4.353	0.0371	4.221	4.422
LFOS	2.875	0.118	2.565	3.078
LFDI	17.98	1.721	12.89	21.10

3.3 Empirical Framework and Estimation Method

Several inferential estimation methods were adopted to estimate the results more precisely. Figure 1 showed the steps of the estimation technique employed in this study.

3.3.1 Unit Root Test

Before proceeding to further in-depth investigation, it is fundamental to look into the integration series. In this way, we apply unit root tests to assess the series' integration properties. First, the study used conventional *"augmented Kapetanios, Shin & Snell (KSSUR) [50], Kwiatkowski–Phillips–Schmidt–Shin (KPSS) [51], and Augmented Dickey-Fuller [52]"* unit root tests. Secondly, conventional unit root tests may provide misleading findings if there is a structural break(s) in the series being tested. So, we adopted the Zivot and Andrews [53] (ZA) unit root test, which may capture both the stationary aspects of the series and a single structural break (s).

3.3.2 ARDL model

To measure the series' co-integration, we used the ARDL bounds test. The following are the reasons why Pesaran et al. [48] limits test is favored over other co-integration tests. The first advantage is that it may be adopted when series are incorporated in mixed order; the second is that it is much more trustworthy, notably for a limited sample; and the third is that it provides accurate estimates of the long-term model. Equation 4 illustrates the ARDL limits test:

$$\Delta LCO_{2_t} = \vartheta_0 + \pi_1 \mathrm{LCO}_{2_{t-1}} + \pi_2 LGDP_{t-1} + \pi_3 LPOP_{t-1} + \pi_4 LFDI_{t-1} + \pi_5 LREN_{t-1} + \pi_6 LFOS_{t-1} + \sum_{i=1}^{w} \vartheta_1\, \Delta CO_{2_{\mathrm{t-i}}} + \sum_{i=1}^{w} \vartheta_2\, \Delta \mathrm{LGDP_{t-i}} + \sum_{i=1}^{w} \vartheta_3 \Delta \mathrm{LPOP_{t-i}} + \sum_{i=1}^{w} \vartheta_4\, \Delta\, LFDI_{t-i} + \sum_{i=1}^{w} \vartheta_5 \Delta \mathrm{LREN_{t-i}} + \sum_{i=1}^{w} \vartheta_6 \Delta \mathrm{LFOS_{t-i}} + €_t \quad (4)$$

No cointegration (the null hypothesis) is contrasted with evidence of cointegration (the alternative hypothesis). If the F-statistic exceeds the threshold values for the upper and lower limits, we cannot accept the null hypothesis. Null and alternative hypotheses are shown in Equations 5 and 6:

$$H_0 = \vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 \quad (5)$$

$$H_1 = \vartheta_1 \neq \vartheta_2 \neq \vartheta_3 \neq \vartheta_4 \neq \vartheta_5 \neq \vartheta_6 \quad (6)$$

H_1 stands for the alternative hypothesis and H_1 for the null hypothesis.

We used the ARDL method after establishing that the parameters are co-integrated. Engle and Granger's [54] error correction model (ECM) is applied to evaluate short-term correlations and the “Error Correction Term” after that the long-term associations have been established. Equation 7 is employed for the long-run ARDL estimation.

$$\Delta LCO_{2t} = \vartheta_0 + \sum_{i=1}^{w} \vartheta_1 \Delta \mathrm{LCO}_{2_{\mathrm{t-i}}} + \sum_{i=1}^{w} \vartheta_2 \Delta \mathrm{LGDP_{t-i}} + \sum_{i=1}^{w} \vartheta_3 \Delta \mathrm{LPOP_{t-i}} + \sum_{i=1}^{w} \vartheta_4 \Delta\, LFDI_{t-i} + \sum_{i=1}^{w} \vartheta_5\, \Delta \mathrm{LREN_{t-i}} + \sum_{i=1}^{w} \vartheta_6 \Delta \mathrm{LFOS_{t-i}} + \ell ECT_{t-i} + €_t \quad (7)$$

Where speed of adjustment is denoted by ℓ

We have employed the fully modified (FMOLS) [55] and dynamic OLS (DOLS) [56] and canonical correlation regression estimator (CCR) estimation approach to visualize the long-run effect of GDP, POP, REN, FDI, and FOS on CO_2 as a robustness check to the ARDL long-run guesstimate. Using these techniques, it is possible to establish asymptotic coherence while taking serial correlation into account. FMOLS and DOLS should only be used when there is corroboration of cointegration between the series. As a result, this research calculates long-term elasticity using FMOLS and DOLS estimators. As follows The FMOLS equation is shown by Equation 8;

$$\Delta LCO_{2_t} = ɤ_0 + ɤ_1 LGDP_t + ɤ_2 LPOP_t + ɤ_3 LFDI_t + ɤ_4 LREN_t + ɤ_5 LFOS_t + \sum_{i=1}^{w} ɋ_1\, \Delta CO_{2_{t-i}} + \sum_{i=1}^{w} ɋ_2\, \Delta \mathrm{LGDP}_{t-i} + \sum_{i=1}^{w} ɋ_3 \Delta \mathrm{LPOP}_{t-i} + \sum_{i=1}^{w} ɋ_4\, \Delta\, LFDI_{t-i} + \sum_{i=1}^{w} ɋ_5 \Delta \mathrm{LREN}_{t-i} + \sum_{i=1}^{w} ɋ_6 \Delta \mathrm{LFOS}_{t-i} + €_t \quad (8)$$

Where t illustrates the timing trend and SIC is used to indicate the lag order. The advantage of FMOLS and DOLS is that they address the issues of endogeneity, auto-regression, and bias resulting from sample bias.

3.3.3 Robustness Check

This study employed the FMOLS, DOLS, and CCR to compare how time-varying factors affected the environment, which allowed us to evaluate the model's robustness. There were two primary factors that necessitated the employment of such methods. The cointegration criterion for parameters must be satisfied before the FMOLS, DOLS, or CCR may be used. Moreover, these methods deal with endogeneity and serial correlation biases brought on by the cointegration interaction. Consequently, it yields outcomes with asymptotic efficiency.

3.3.4 Pairwise Granger Causality Test

As there is a possibility that theoretical correlations won't work in real life due to certain components that might not be well stated in theory, the concept of a causality test would determine whether past changes in a factor are to cause of the current observation or not. It is claimed that causation extends from X to Y if the sum of X's past and current values deviates considerably from zero. Similar rules apply to Y and X causality; if the results vary from zero, then causation is present on both sides. To determine if the factors had a short-term causal connection, the investigation used the paired Granger causality [57] test. The following equation (6) demonstrates the causal connection between Xt and Yt:

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

Here, Jt denotes the data sets derived from the preceding observations acquired until that point in time (t).

3.3.5 Diagnostic test

The investigation used a variety of different diagnostic techniques to confirm the precision of the findings. In this study, heteroscedasticity was determined using the ARCH test [58], specification error was assessed using the Ramsey Reset test [59], autocorrelation was ascertained using the Durbin Watson test [60], normality was determined using the Jarque-Bera test [61], and predicted model stability was identified using the CUSUM & CUSUMsq test [62]. Table (9) provides an overview of the findings of the diagnostic approaches.

4. Empirical Findings

4.1 Unit Root Test Result

First, we check the parameters' stationarity characteristics to determine sure they are suitable for use in this empirical study. Based on this, we used unit root tests (KSSUR, KPSS & ADF) to agree on whether or not the series was stationary. The findings of the "unit root tests" are portrayed in Table (3). The results of the stationarity test demonstrated that the variables used in this study had a non-uniform order of integration, which favors the ARDL method over the traditional cointegration-based methods. Table (3) showed that, while all variables [LCO_2, LGDP, LPOP, LFDI, and LFOS] exhibits I(1), only LREN showed Integrated to Zero or I(0). Thus, the variables employed in this study have mixed order of integration.

Table 3: Unit Root Tests

Variable	*KSUR Test*		*ADF Test*		*KPSS Test*		*Remark*
	Level	*1st Dif.*	*Level*	*1st Dif.*	*Level*	*1st Dif.*	*Stationary at*
LCO2	*-0.12*	*-3.388****	*-0.05*	*-5.52****	*-1.43*	*-6.99****	*I (1)*
LGDP	*2.19*	*-4.38****	*2.45*	*-3.53****	*0.94*	*-7.73****	*I (1)*
LPOP	*2.015*	*-3.53****	*2.19*	*-3.38****	*1.81*	*-7.31****	*I (1)*
LREN	*-5.52****		*-5.52****		*-4.49***		*I (0)*
LFOS	*-0.12*	*-6.05****	*-0.05*	*-6.51****	*-0.712*	*-6.92****	*I (1)*
LFDI	*-4.14***		*-4.05****		*-4.58***		*I (0)*

(a) The asterisk symbols (***& **) are utilized for 1% &5% significance levels. (b) Optimal lag selected by AIC & SIC criterion.

4.2. Structural break analysis

Table 4: Structural Break Analysis

Zivot-Andrews test						
Variables	*ZA stat.*	*Break*	*1%*	*5%*	*10%*	*Decision*
LCO_2	*-3.075****	*2005*	*-5.34*	*-4.93*	*-4.58*	*Break Exist*
LGDP	*-2.649****	*1991*	*-5.34*	*-4.93*	*-4.58*	
LPOP	*-3.702***	*2012*	*-5.34*	*-4.93*	*-4.58*	
LREN	*-5.568*	*1991*	*-5.34*	*-4.93*	*-4.58*	
LFOS	*-3.839****	*2005*	*-5.34*	*-4.93*	*-4.58*	
LFDI	*-4.299****	*2013*	*-5.34*	*-4.93*	*-4.58*	

Assuming that the mean, variance, and trend will not change over time is the stationarity assumption, which forms the foundation for applied time series prediction and assessment. A structural break is believed to have happened if any of the aforementioned conditions altered, or if the break period fell within the sample period. In econometrics, a structural break is a sudden shift in the time series data. Large discrepancies in forecasts and inconsistencies in theoretical frameworks may come from it. Zivot-Andrews unit root testing was used in this research to spot the abrupt change in trend. Figure 4 depicts the test results, which indicate that the statistical sample has a substantial structural breakdown. The outcomes depicted in Table 4 also present that LCO_2, LGDP, LPOP, LFOS, and LFDI observed significant structural breaks in 2005, 1991, 2012, 2005, and 2013, accordingly.

4.3. ARDL Bound Test

Table 5: ARDL Bound Test

	Test Statistics	*Value*	*K*	
	F statistics	*0.936*	*5*	
	Significance level			
Critical Bounds	*10%*	*5%*	*2.50%*	*1%*
I(0)	*2.26*	*2.62*	*2.96*	*3.41*
I(1)	*3.35*	*3.79*	*4.18*	*4.68*

F-statistics are estimated and compared to the critical values evaluated by Pesaran et al. [48] to determine whether or not the null hypothesis should be rejected. If the intended F stat. goes over the tabulated F value, we may reject the null hypothesis such as no cointegration exists. If the calculated F stat has a lower value than the tabulated value, it fails to reject the developed hypothesis. No inference can be made from the data, however, if the F-statistics value falls inside the bounds. A close inspection of Table 5 reveals that the F-statistic is statistically significant at the 1% level. Thus, significant long-run linkage exists between explanatory and dependent variables. Also, F-value is much higher than the formula's upper limit. In light of new information on China's history, we can assess the impact of factors like GDP, population, FDI, and renewable and fossil fuel energy usage on CO_2 emissions in China.

4.4. ARDL Long and Short-Run Results

ARDL long-run (LR) and short-run (SR) assessments are depicted in the Table (6) and showed how various factors are connected with CO_2 emission in China. Long-run (LR) estimation results presented that coefficients of LGDP are negative and highly significant at a 5% level of significance. The coefficient value of LGDP is -0.0461 and implies that a 1% increase in LGDP would result in reducing CO_2 emission by 0.0461% in the long run and vice versa. Similarly, the marginal effect of LPOP has significant to boost emission where more population contacts more pollution. The result entail that a 1% enlarges in populace will cause higher emissions in the long run by 0.199% and vice versa. Additionally, the value of LREN is -12.26 and which is significant at a 5% significance level. Thus, a 1% increase in LREN will reduce the LCO_2 by 12.26% in the long run. Finally, the estimation result of ARDL also showed that the value of LFOS and LFDI are 2.398 and -0.139. The value of LFOS and LFDI does not affect China's long-term CO_2 emissions.

Table 6: ARDL Long-Run and Short-Run Results

VARIABLES	LR	SR
LGDP	-1.0461*(0.63)	
LPOP	0.199**(0.089)	
LFOS	2.398(4.91)	
LREN	-12.26***(1.509)	
LFDI	-0.139(0.818)	
D.LGDP		-0.371**(0.145)
D.LPOP		-1.330(8.293)
D.LFOS		0.361(0.265)
D.LREN		-3.727***(1.287)
D.LFDI		-0.00253(0.0074)
ECT (Speed Adjustment)		-0.450***(0.125)
Constant		-5.264(5.868)
R-square	0.654	

(a) Asterisk symbol (***, **,*) utilized for 1% ,5%& 10% significance level. (b) S E in brackets.

The findings of Short-run (SR) ARDL estimation also showed in the Table (6). The result showed that the coefficient value of LGDP is -0.371 which is tended GDP has no cause to enlarge emission in the SR. Thus, a 1% increase in LGDP will lower emissions in the short run. Moreover, the results depicted in Table (6) showed that the value of LREN is -3.727 and which is highly significant at a 1% significance level. Therefore, a 1% extend in LREN will lower the CO_2 emission by 3.727% in the short run and similar sign of this coefficient was found by Rahman and Majumder [63]. Furthermore, the value of LPOP and LFOS are -1.330 and 0.361. The values of LPOP and LFOS have an insignificant impact on CO_2 emissions in the short run. Additionally, the L.LCO$_2$ coefficient is positive for the chosen variables, and there is a yearly divergence of 0.0267% between the SR and LR equilibrium. The speed of adjustment is -0.45% means 45% to move forward the factors in an equilibrium situation.

4.5. Robustness Check and Causality Test

We also employed several estimation approaches such as FMOLS, DOLS, and CCR to observe the robustness of ARDL estimation findings. The results of FMOLS, DOLS, and CCR are recorded in Table (7). The upshots of the DOLS showed that the estimated value of LGDP is -1.811 and which is highly significant at a 1% level of significance. Thus increase in LGDP will significantly lower the CO_2 emission and this ruling is reliable with the outcomes of ARDL results. Similarly, the coefficient value of LPOP is positive and highly significant at a “1% level of significance under the FMOLS, DOLS, and CCR estimation” approach. The result implies that an increase in LPOP also triggers the emission of CO_2 and these results are also reliable with the findings of the ARDL estimation approach. Moreover, the coefficient value of LREN is negative and significant under FMOLS and DOLS approaches. Rahman and Majumder [63] found LREN was negative coefficient by using FMOLS model in N-11 countries. The negative association between LREN and LCO2 also corroborated the results of the ARDL estimation approach. The findings of FMOLS, DOLS, and CCR assessment showed that the coefficient value of LFDI is insignificant and this results in line with the ARDL estimation technique. Thus, the ARDL estimation results are robust and this result is consistent with the findings of FMOLS, DOLS, and CCR approaches.

The results of the paired Ganger causality test are shown in Table 8. The null hypothesis of no causality is rejected if F-statistics are significant. Table (8) demonstrates a one-way causation presence between LCO2 and LGDP, and LFOS and LCO2. In addition, there are also bidirectional causal relationships exist between LREN and LCO2, and LFDI and LCO2.

Table 7: Robustness Check

Variables	*FMOLS*	*DOLS*	*CCR*
LnCO2 dependent			
LGDP	*-0.642 (0.814)*	*-1.811*** (0.406)*	*0.627* (0.346)*
LPOP	*0.478***(0.145)*	*0.767***(0.131)*	*0.463***(0.166)*
LREN	*-3.558** (1.573)*	*-10.849*** (1.214)*	*-2.980 (3.003)*
LFOS	*1.254*** (0.438)*	*0.174 (0.213)*	*1.289** (0.478)*
LFDI	*0.028 (0.022)*	*0.009 (0.014)*	*-0.031 (0.030)*
C	*16.843*	*55.318*	*14.335*
R-squared	*0.733*	*0.982*	*0.725*

(a) Asterisk symbol (***, **,*) utilized for 1% ,5%& 10% significance level; (b) SE in brackets.

Table 8: Granger Causality Test Outcomes

Null Hypothesis:	*F-Statistic*	*Prob.*
LGDP $\neq LCO_2$	*0.85918*	*0.4307*
$LCO_2 \neq$ *LGDP*	*5.40911*	*0.008*
LPOP $\neq LCO_2$	*0.55552*	*0.5778*
$LCO_2 \neq$ *LPOP*	*2.10907*	*0.1337*
LREN $\neq LCO_2$	*8.40584*	*0.0008*
$LCO_2 \neq$ *LREN*	*3.23988*	*0.0489*
LFOS $\neq$ *LCO2*	*4.14323*	*0.024*
$LCO_2 \neq$ *LFOS*	*0.15757*	*0.8548*
LFDI $\neq LCO_2$	*3.51271*	*0.0388*
$LCO_2 \neq$ *LFDI*	*5.0728*	*0.0106*
LPOP $\neq$ *LGDP*	*1.21214*	*0.3075*

(a) Asterisk symbol (***, **,*) utilized for 1%, 5%& 10% significance level. (b) Optimal lag selected by AIC & SIC criterion.

4.7 Outcomes of Diagnostic Tests

Finally, we think it's important to address how well the ARDL error correction model fits the data. Multiple diagnostic and stability analyses were performed with this goal in mind.

Table 9: Diagnostic tests for Model adequacy

Test	*Null Hypothesis*	*Test Statistic*	*P-Value*
AECH Heteroskedasticity test	*Ho: Homoskedasticity*	*0.425 (F- statistic)*	*0.254*
Normality/Jarque Bera	*Ho: residuals have a normal distribution.*	*0.7854*	*0.3785*
B-G LM test	*Ho: No serial correlation up to 2 lags*	*2.142 (F- statistic)*	*0.190*
R^2			*.784*
Adjusted R^2			*.841*
DW value		*1.854*	
Ram. RESET (F)	*Ho: The model's functional form is valid.*	*3.192 (F- statistic)*	*0.086*

Homoscedasticity, heteroscedasticity, Serial correlation, normalcy, and model specification are all examined by the diagnostic tests. According to the findings in Table 9, the model is not challenged by measurement errors, heteroscedasticity, autocorrelation, or normalcy. This makes it clear that the findings of this inquiry can be used to reliably draw conclusions. Figure (2) portrayed the outcomes of the CUSUM and CUSUM square test and indicates that the blue line lies within the red lines at a 5% level of significance and makes the parameters of the estimated model stable.

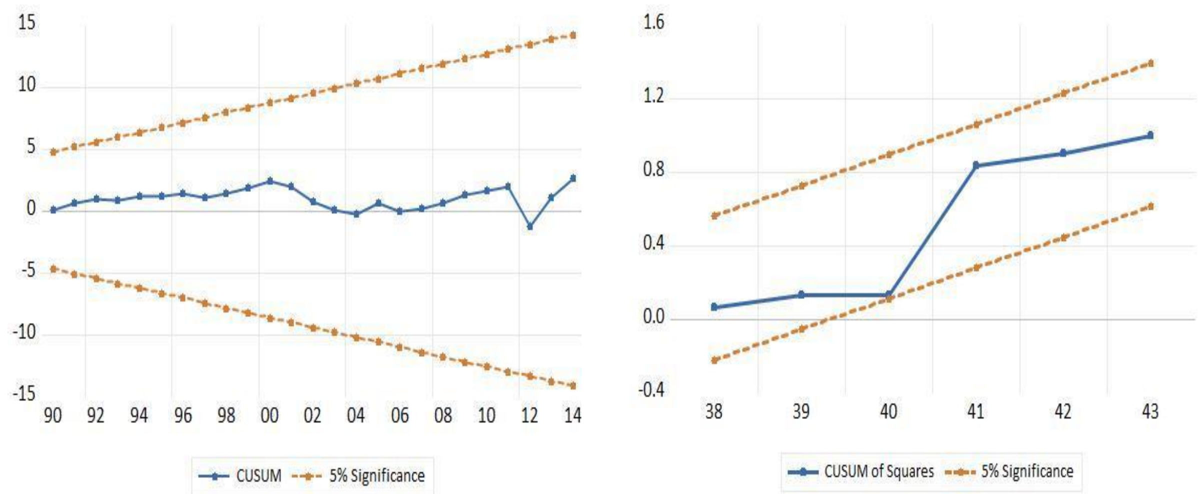

Figure 2: CUSUM and CUSUM Square Tests

5. Conclusion

This research examined the influence of economic growth, energy usage, and FDI on China's CO_2 emission using data from 1972 to 2021. This study used the KSSUR, ADF, and KPSS unit root tests to determine the stationary characteristic within the dataset. The results of those tests indicated that variables displayed mixed-order integration. The Zivot-Andrewes unit root test was also used in this research to identify the structural break within the sample period, and the findings of this study demonstrated the existence of a substantial structural break within the sample period. To guarantee the validity of the results, the inquiry utilized the FMOLS, DOLS, and CCR long-run estimators in addition to the ARDL model. According to ARDL long-term estimates, economic development increases CO_2 emissions, but the use of renewable energy reduces CO_2 emissions over time. These findings were also supported by FMOLS, DOLS, and CCR estimate outputs. The usages of fossil fuels for energy, population growth, and FDI have minimal impact on China's carbon emissions. The results indicate that China will need more renewable energy sources in the future. China's CO_2 emissions are pushed up by the growing GDP, expanding FDI size, and substantial increase in population. China needs to identify the factors that contribute most to the nation's CO_2 emissions at this time. The major objective is to identify the principal contributors to CO_2 emission. Then consider using more sustainable energy sources and using less fossil fuel energy. Several diagnostic tests, such as the Breush pagan Godfrey test, Jarque Bera test, Breush Godfrey LM test, and CUSUM & CUSUMSQ test to check model adequacy and certify that the model is devoid of all forms of problematic conditions.

6. Policy Implication

Carbon dioxide (CO_2) emissions can be reduced by encouraging sustainable economic growth and decreasing reliance on fossil fuels, both of which can be measured using GDP. To lessen reliance on fossil fuels and GHG, GDP can incentivize the research, development, and deployment of renewable sources including solar, wind, and hydro power. Companies that put money into renewable energy sources should be rewarded monetarily for their efforts. Corporations that put money into renewable energy should be rewarded monetarily for their efforts. In order to encourage businesses and individuals to decrease their carbon footprint, a carbon tax should be imposed on the production and consumption of fossil fuels. Revenue from the carbon tax can be used to fund initiatives to expand access to renewable energy sources and strengthen regulatory safeguards for the planet. Investment in infrastructure and monetary incentives for users are two ways GDP can promote eco-friendly means of transportation including public transit, biking, and walking. Global economic growth can encourage nations to work together to solve climate change by facilitating the sharing of innovative solutions, the transfer of cutting-edge technologies, and concerted action on environmental concerns. By offering fiscal incentives like tax credits and subsidies, GDP may promote the development of low-carbon businesses like electric vehicles, energy storage, and clean energy. Emissions of carbon dioxide (CO_2) can be heavily influenced by population numbers and habits. The promotion of family planning and reproductive health can be aided by lowering financial, institutional, and societal barriers to these issues. As a result, population growth will be slowed and energy consumption will decrease. Encourage people to adopt sustainable lifestyles that lessen their reliance on fossil fuels and their contribution to global warming by spreading information on the effects of individual actions. By encouraging investment in low-carbon businesses and technology, FDI can help reduce emissions. Offering tax breaks, subsidies, and other financial incentives to foreign direct investment in low-carbon businesses like renewable energy, energy efficiency, and sustainable transportation is a good start. To ensure FDI projects have a negligible effect on the environment and aid in the reduction of CO_2 emissions, it is important to implement environmental guidelines for them. Keep an eye on foreign direct investment projects to make sure they're helping the planet and cutting down on carbon emissions.

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